USING BIODATA TO PREDICT ALTERNATIVE MEASURES OF TRAINING PERIOD TURNOVER

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USING BIODATA TO PREDICT ALTERNATIVE
MEASURES OF TRAINING PERIOD TURNOVER

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Logistic Regression was utilized to add to what is known about biodata and turnover. Biodata items from 958 former and current employees in a manufacturing environment were used to develop models to predict a) which employees will turnover prior to completion of a ninety-day training period, b) who will leave voluntarily versus involuntarily, and of those who leave voluntarily c) which leavers are functional versus dysfunctional. A significant relationship was found between biodata items and completion of the ninety-day training period. The resulting model indicated that those who completed training were employed at time of hire, had higher aptitude scores, and had a previous address close to the plant. In addition, those who left voluntarily had higher levels of performance than involuntary leavers. However, biodata items did not differentiate between

voluntary and involuntary leavers or between functional and dysfunctional leavers.

Using Biodata to Predict Alternative
Measures of Training Period Turnover

One of the greatest challenges facing managers of human resources is the recruitment, selection, and retention of high quality employees. Numerous researchers have testified to the significance of turnover as a problem and the need to reduce it where possible (Balfour & Neff, 1993; Cascio, 1976; Dalton, Krackhardt, & Porter, 1981; Lefkowitz & Katz, 1969; Mosel & Wade, 1951; Parasuraman, 1989; Porter & Steers, 1973; Schuh, 1967a; Shott, Albright, & Glennon, 1963). Balfour and Neff (1993) state that turnover rates greater than twenty percent are a direct threat to the human capital and effectiveness of an organization.

A substantial amount of time and financial resources could be saved by the reduction of certain types of turnover. In fact, it has been estimated that the cost to replace a single non-managerial employee is about $2,500 (Mirvis & Lawler, 1977). In addition, the retention of quality employees is especially crucial when the pool of qualified replacements is limited. Many of the factors that influence whether an employee remains with an organization (e.g., labor market conditions, alternative types of employment, wage rates, working conditions) are not always controlled by human resource managers. However, these managers do have control, at least to some degree, over who is selected from an applicant pool for entrance to the organization.

The obvious goal of selection is to choose individuals who will remain with an organization and maintain acceptable levels of performance. One approach to this end is the use of biographical data (biodata) or personal history information which can be found on application blanks and in personnel files. While this approach may not include all possible factors that influence turnover (e.g., labor market conditions), it has been found to be an effective method for reducing turnover. Cascio (1976), for example, discussed using biodata as an "early warning system" which can forecast short-term employees prior to selection.

The purpose of this study is two-fold. First, this early warning system will be applied to an organization in which the majority (i.e., seventy-two percent) of turnover occurs prior to the completion of a ninety-day training period. Once employees complete the ninety-day training period, the probability of turnover drops sharply (i.e., twenty-eight percent). Biodata will be gathered from previous employee files (e.g., data on application blanks; interest and personality questionnaires; intelligence measures, performance reviews) in order to develop a prediction model which may reduce turnover by enabling the pre-hire identification of applicants most likely to terminate.

While several researchers, such as Cascio (1976) and others reviewed below, have attested to the relationship between biodata and turnover and biodata's potential to reduce turnover, others have raised issues regarding how the turnover criterion is operationalized. The second purpose of this study is to address some of these criterion problems. First, a clear distinction between voluntary and involuntary turnover should be made. This distinction would enable a better understanding of both types of turnover and make possible the study of which biodata items are related to each type of turnover. Mobley, Griffeth, Hand, and Meglino (1979); Wells and Muchinsky (1985); and Lefkowity and Katz (1969) have noted that the bulk of turnover research centers on voluntary turnover and that involuntary turnover has, for the most part, been ignored. In addition, other studies have failed to document which type of turnover, voluntary or involuntary, was being studied.

Second, in order to more accurately address the turnover problem, a classification of effective and ineffective voluntary leavers is needed. Porter and Steers(1973) and Dalton, Krackhardt, and Porter(1981) have suggested further investigation and classification of turnover based on the premise that not all turnover is negative and that some may in fact be beneficial to the organization.

In sum, this researcher will attempt to add to what is known about the relationship between turnover and biodata. To reach this end, several models will be developed to predict (a) which employees will turnover prior to the completion of a ninety-day training period, (b) who will leave voluntarily versus involuntarily, and of those who leave voluntarily (c) which leavers are functional versus dysfunctional.

The following section is a review of the literature dealing with biodata, turnover, and additional related variables. The review begins with the theoretical rational for the use of biodata in selection including the Ecological Theory of Biodata, Social Identity Theory, and the domain of biodata. This discussion is followed by an examination of the relationships between turnover, various biodata items, and related variables. Finally, an account of the criterion problems regarding turnover research will be given. This account will include a discussion of the voluntary versus involuntary turnover distinction, effective versus ineffective leavers, and functional versus dysfunctional voluntary turnover.

Theoretical Basis For Use of Biodata

Owens (as cited in Mael, 1991) states that one of the fundamental principles of measurement is that the best predictor of what a person will do in the future is what they have done in the past. This rationale has been expanded into the Ecology Model of Biodata (Mael, 1991) which holds that all individuals begin life with certain hereditary and environmental resources and limitations that determine individual differences. Mael (1991) states that individuals strive to maximize their adaptation to the environment through learning and cognition. Decisions regarding work and careers are made based on the perceived value of their outcomes. This value reflects individual needs and values so that choices will reflect preexisting individual characteristics. Additionally, each individual has a frame of reference, or template, that reflects an idealized image of how life should proceed and which in turn drives one's beliefs about one’s self and world in general.

After initial choices have been made, subsequent adaptation is required in order to attain desired goals in a specific situation (Mael, 1991). A cycle of choice, development, and adaptation begins and thus leads to additional choices as a result of more clearly perceived means of need and value satisfaction. Those who are successful seek out a variety of situations to satisfy all needs and values. A cohesive pattern of choices develops through this process. Thus, when predicting an individual's performance in the future, a wide variety of previous behaviors can contribute to the prediction of subsequent choices and performance--even if only indirectly.

The Ecology Theory of biodata is supplemented by the Social Identity Theory (SIT) (Mael, 1991; Mael & Ashforth, 1995). SIT holds that everyone has a self-concept made up of personal identity and social identity. Personal identity is comprised of personal attributes such as bodily features and disposition. In contrast, social identity includes those self-defining dimensions of a person that are expressed in terms of psychologically belonging to a perceived social category (e.g., nationality, political or social affiliations). Thus, the groups to which individuals belong contribute to the development of a sense of who one is, what his/her goals and attributes are, and what one ought to do. For example, one's birthplace, teams or clubs one joins, or the occupation of one's parents each suggest a set of values, aspirations, and self-perceptions unique to that social category. Therefore, each experience that classifies an individual has the potential to shape behavior patterns, which--in turn--make future behavior more predictable.

Biodata Defined

Mael (1991) states that the domain of information used to predict future behavior is quite large. Based on the consolidation of the ecology model and SIT, any event or behavior that has occurred whether reflecting capabilities existing previously or those shaping behavior itself is appropriate subject matter for biodata items. Biodata items may even include items that measure temperament because the domains of these items overlap and cannot be separated from one another. Mael continued by stating that the sole defining characteristic of a biodata item is that it reflects a part of a person's current or past life history.

However, several attributes of biodata are suggested. First, biodata should be historical (Mael, 1991; Asher, 1972). More specifically, biodata should pertain to events that have taken place or continue to take place. Items that measure behavior intentions in hypothetical situations, while admissible, should be scrutinized to limit distortion.

Second, the more external, objective, first-hand, discrete, and verifiable biodata are the more they ensure correct reporting of behaviors (Mael, 1991; Asher, 1972). Mael (1991) found that objective events were preferable because of the probability of faking and self-distortion of less verifiable, subjective events. Asher (1972) found hard (i.e., objective) biodata items had greater validities than soft (i.e., subjective) items.

Similarly, biodata should be first-hand in that the use of subjective speculation, such as how a third party would rate an individual's performance, would be even less objective. Discrete actions such as number of jobs held or age at first job are typically more accurate than summary responses (e.g., average time spent studying), which require computation or estimation and, therefore, have more chance for error. Biodata items should also be limited to those that can be corroborated from an independent source.

Finally, for legal and ethical reasons, Mael (1991) has suggested the consideration of several other attributes of biodata. First, one should consider the controllability of the event being measured. For example, it may be unethical to include noncontrollable items pertaining to physical characteristics that are not job related. In addition, the accessibility of the skill or experience used should be considered in order to ensure item fairness (e.g., not everyone has had the opportunity to play varsity football). Even though virtually all life experiences are potentially relevant, items lacking at least some job relevance may be open to legal scrutiny. These attributes of biodata (i.e., controllability, accessibility, job relevance) should be taken into account when selecting items; however, they should not be viewed as absolutes. Direction on the content of biodata items has also been given by Hogan (1994).

Mumford and Owens (as cited in Hogan, 1994) recommended that the item content of background data or biodata should primarily deal with past behavior and experiences, that items dealing with family relationships are usually viewed as offensive, that items and response options should be specific and brief, and that items concerning past and present behaviors as well as with opinions, attitudes, and values are normally admissible. These recommendations may be viewed as less stringent when compared to the taxonomy of Mael (1991). However, Hogan (1994), when reviewing Mael's guidelines, reminds the reader that the first attribute (i.e., historical) is the only necessary defining attribute of biodata items and that Mael points out that the other attributes involve tradeoffs between fulfilling legal obligations, reducing faking, and preserving a suitable item pool to cover the domain of interest. With Hogan's comments in mind, independent variables such as interest inventories, personality questionnaires, and aptitudes measures are within the acceptable domain of biodata.

With the established problem of turnover and the conceptual rationale for biodata presented, it is next appropriate to discuss what if any relationship exists between turnover and biodata.

Relationship Between Selected Biodata Items and Turnover

Numerous researchers have examined the relationship between biodata and turnover (Arnold & Feldman, 1982; Balfour & Neff, 1993; Black & MacKinney, 1963; Brown &

Ghiselli, 1947; Buel, 1964; Campion & Mitchell, 1986; Cascio, 1976; Cotton & Tuttle, 1986; Healy, Lehman, & McDaniel, 1995; Kerr, 1947; Kirchner & Dunnette, 1957; Kriedt & Gadel, 1953; Mael & Ashforth, 1995; MacKinney & Wolins, 1959; Michaels & Spector, 1982; Mobley, Griffeth, Hand, & Meglino, 1979; Mosel & Wade, 1951; Parasuraman, 1989; Porter & Steer, 1973; Reilly & Chad, 1982; Rothstein, Schmidt, Erwin, Owens, & Sparks, 1990; Scott & Johnson, 1967; Schuh, 1967b; Schwab & Oliver, 1974; Shott, Albright, & Glennon, 1963; Waters, Roach, & Waters, 1976) and have found many biodata items are related to turnover. While certain biodata items have received more attention than others, the following is a summary of the biodata items most frequently related to turnover.

Age and Turnover.

One of the most studied biodata items is age (Arnold & Feldman, 1982; Balfour & Neff, 1993; Black & MacKinney, 1963; Brown & Ghiselli, 1947; Cotton & Tuttle, 1986; Healy, Lehman, & McDaniel, 1995; Kriedt & Gadel, 1953; Michaels & Spector, 1982; Mobley, Griffeth, Hand, & Meglino, 1979; Parasuraman, 1989; Porter & Steers, 1973; Stumpf & Dawley, 1981; Waters, Roach, & Waters, 1976). Porter and Steers

(1973) in a summary of over ten years of research on turnover found age to be strongly and negatively related to turnover. Similarly, Mobley, Griffeth, Hand, and Meglino (1979) found age to be consistently and negatively related to turnover. A meta-analysis of employee turnover research conducted by Cotton and Tuttle (1986) also found age to be negatively related to turnover. The above studies summarize the finding of the majority of research exploring the relationship between turnover and age; however, one recent meta-analytic study suggests that the relationship between age and voluntary turnover is weak if it exists at all (Healy, Lehman, & McDaniel, 1995).

While most studies report the magnitude of the correlation between turnover and age to be between -.20 and -.25 (Arnold & Feldman, 1982; Stumpf & Dawley, 1981; Waters, Roach, & Waters, 1975) and as high as -.55 (Black & MacKinney, 1963), Healy, Lehman, and McDaniel (1995) found a near zero relationship (i.e., -.08). The explanation given for this discrepancy by Healy et al. (1995) is that past reviews have deficient methodology (i.e., sampling error, nonrepresentative sampling of studies, use of vote-counting method in meta-analysis). By employing the meta-analysis methods of Hunter and Schimdt, Healy et al. (1995) corrected the data for artifactual sources of variance and shed a considerable doubt on what was thought to be a solid relationship between turnover and age. Based on the findings of this latest research, the relationship between age and turnover appears to be the result of statistical artifacts and does not exist once these artifacts are taken into consideration.

Tenure and Turnover.

Like age, tenure or length of service in an organization is one of the most highly studied variables in turnover research (Arnold & Feldman, 1982; Balfour & Neff, 1993; Campion & Mitchell, 1986; Cotton & Tuttle, 1986; Michaels & Spector, 1982; Mobley, Griffeth, Hand, & Meglino, 1979; Parasuraman, 1989; Porter & Steers, 1973; Stumpf & Dawley, 1981; Waters, Roach, & Waters, 1976). The bulk of literature on biodata, as well as three of the major reviews of this research (Cotton & Tuttle, 1986; Mobley et al, 1979; Porter & Steers, 1973), found tenure to be negatively related to turnover. The magnitude of the correlations where reported were typically in the range of -.30 to -.35 (Arnold & Feldman, 1982; Stumpf & Dawley, 1981; Waters, Roach, & Waters, 1976).

While the majority of the research exploring the relationship between tenure and turnover defined tenure as length of service on a current job, some have looked at previous tenure and how it predicts turnover on a current job (Porter & Steers, 1973; Shott, Albright, & Glennon, 1963). These studies also found previous tenure to be negatively related to turnover. This finding is in line with the premise of Owens (Mael, 1991) that the best predictor of future behavior is past behavior.

Several studies of turnover and tenure involve the use of weighted application blanks (WAB) to predict employee tenure (Buel, 1964; Cascio, 1976; Kirchner & Dunnette, 1957; Scott & Johnson, 1967; Schwab & Oliver, 1974; Shott, Albright, & Glennon, 1963; Mosel & Wade, 1951). In these studies application blank items are assigned weights in order to maximize differentiation between criterion groups (i.e., long versus short tenure). The magnitude of the correlations between WAB scores and tenure ranged from .33 to .79. Reviews of the literature by Reilly and Chao (1982) and Schuh (1967a) also found a significant relationship between biodata items and tenure. Reilly and Chao (1982) concluded that objective biodata items such as age, martial status, and number of dependents were found to be consistent and valid predictors of tenure.

In spite of the abundance of research demonstrating a relationship between biodata and tenure, at least two studies failed to support this relationship. Brown and Ghiselli (1947) utilized biodata items to predict accident rate and months on the job. Of the variables studied, only age and marital status had any relationship to tenure (i.e.; age, $r = .21$ and married had slightly more tenure). Because the relationship between the other variables and tenure were not different from zero, a weighted combination was not used. Schuh (1967b) in a study of salesmen over a five year period found that while some biodata items were related to tenure in specific years, none were significant predictors over the entire period. The relationship between biodata items and tenure for specific years was explained to be a product of sampling error.

In sum, the biodata research which explores tenure and turnover supports a negative relationship between tenure and turnover, as well as a significant relationship between biodata items (e.g., number of dependents) and tenure.

Gender and Turnover.

The relationship between gender and turnover has been less than clear. Several studies have found that females were more likely to leave than males. This finding included a study by Arnold and Feldman (1982) that examined turnover of accountants, a meta-analysis by Cotton and Tuttle (1986) who looked at this relationship for numerous occupations, and a study of factory labor turnover performed by Kerr (1947). At the same time, Stumpf and Dawley(1981) found male bank tellers to leave at higher rates and Mobley et al.(1973) found the relationship to be inconclusive in a review of the literature.

Family Responsibility and Turnover.

In a review of over ten years of research, Porter and Steers (1973) found an interesting interaction between gender and level of family responsibility, another biodata item found in the literature. Multiple studies found that, for females, as the level of family responsibility increased (i.e., became married or had children) so did the level of turnover. Conversely, other research reported found that for males, turnover decreased as the level of family responsibility increased. It was suggested that the traditional role of husband as bread winner and wife as caretaker was operating as expected. Porter and Steers (1973) raised the question as to whether these roles would continue to be segregated by gender, especially if these roles change and the number of single parent and dual bread winner families increased. Additional research exploring the relationship between family responsibility and turnover found a negative relationship (Arnold & Feldman, 1982; Black & MacKinney, 1963; Cotton & Tuttle, 1986; Mobley et al, 1979). Based on the research cited above, it appears that for most individuals the relationship between family responsibility and turnover should be negative.

Education Level and Turnover.

The education level of an individual has also been discussed in the literature as it relates to turnover. Balfour and Neff (1993) and Wanous (1979) found turnover and education level to be positively related. However, several others found no relationship to exist (Brown & Ghiselli, 1947; Campion & Mitchell, 1986; Stumpf & Dawley, 1981).

Personality and Turnover.

Porter and Steers (1973), in a review of the literature, found personality characteristics related to who leaves an organization. The primary conclusion was that employees who leave are more likely to possess extreme levels of personality traits. Employees who manifest very high degrees of independence, self-confidence, aggressiveness, or who hold high career aspirations, for example, leave more often. Likewise, employees with high levels of anxiety or who are fairly unstable emotionally are more likely to turnover than individuals with traits that cluster close to the center of the continuum. In addition, Schuh (1967a) in a review of biodata literature also found individuals scoring highly on one or more personality scales contained in personality inventories have shorter tenure (e.g., Bernreuter, $r = -.09$; Guilfoird-Zimmerman, $r = -.51$ & $-.55$; and Minnesota Multiphasic Personality Inventory).

Vocational Interest and Turnover.

Vocational interest, like personality characteristics, has been shown to be related to employee turnover. As mentioned in Porter and Steer (1973) and Schuh (1967a), employees who scored highly on interest inventories such as the Strong Vocational Interest Blank (Boyd, 1961; Ferguson, 1958) or the Kuder Preference Record (Mayseke, 1964) terminated less frequently and were more likely to become a long tenure employee.

Another study by Kriedt and Gadel (1953), which looked at turnover after three and twelve months of employment, found clerical workers who scored highly on an interest questionnaire and job preference blank were more likely to stay than leave. Those whose scores on the interest questionnaire indicated a preference for manual, mechanical, and clerical activities, for example, stayed longer ($r = .19$ for both three and twelve month turnover). Similarly, those who scored highly on the job preference blank, which rated the importance of eleven job factors (e.g., type of work), also stayed longer ($r = .33$ for three month turnover and $r = .21$ for twelve month turnover).

Previous Experience and Turnover.

Balfour and Neff (1993) studied turnover of human service employees and found differences in employees who stay and those who leave. In addition to the relationship between turnover and education mentioned earlier, this study also found a relationship between turnover and previous experience. Those most likely to leave were new employees with no previous experience or internship in a human service agency.

Intelligence and Turnover.

Cognitive ability, or intelligence, is included as a biodata variable under the broadest definition (Mael, 1991) and has received significant exposure in the literature as a predictor variable (Hunter & Hunter, 1984). However, in relation to turnover, intelligence has shown only limited promise. While Kriedt and Gadel (1953) found leavers to have significantly higher intelligence than those who stayed after three month and twelve months (i.e., .25 and .21 respectively), most research has found little if any relationship between turnover and intelligence. Brown and Ghiselli (1947) did not find support for the prediction of time on the job with the use of scores from tests of intelligence (i.e., correlation = .09). Schuh (1967b, 1967a) in two studies found zero or no systematic relationship between intelligence and tenure, a variable closely related to turnover.

Relationship Between Biodata and Job Performance

Biodata has also been studied in terms of how it relates to other variables such as job performance. For example, Asher (1972) found biodata items to have vastly superior validity as predictors of job proficiency in comparison to other predictors such as intelligence, aptitude, interest, and personality. Asher looked at studies which utilized scoreable application blanks to predict job behavior. Fifty-five percent of studies employing biodata had validity coefficients of .50 or higher and ninety-seven percent had validity coefficients of .30 or higher with job proficiency. Hunter and Hunter (1984) found that, for entry-level jobs, biodata had an average validity of .37 when supervisory ratings of performance were used as the measure of performance. In a review of employee selection procedures, Reilly and Chao (1982) found that the average validity coefficient between biodata and productivity was .46. Similarly, in a study dealing with the generalizability of biodata, Rothstein, Schmidt, Erwin, Owens, and Sparks (1990) found the mean validity coefficient for biodata with various performance criteria to be .28 and these coefficients generalized across organizations.

Performance, which has been linked to biodata, is also related to who leaves an organization. A meta-analysis of the relationship between performance and turnover by McEvoy and Cascio (1987) revealed that, while some such as Steers and Mowday (1981) had predicted that high performance would lead to higher expectations of rewards and if not met would lead to higher voluntary turnover, the relationship between performance and turnover was generally negative ($r = -.28$). Specifically, good performers are less likely to leave an organization than poor performers. Stumpf and Dawley (1981); Wanous, Stumpf, and Bedrosian (1979); and Wells and Muchinsky (1985) also found a strong negative relationship between performance and turnover. Stumpf and Dawley (1981) and Wanous et al.(1979) found this relationship was stronger for involuntary turnover than for voluntary turnover (i.e., voluntary $r = -.21$ to $-.81$ and involuntary $r = -.39$ to $-.84$). Those promoted or currently employed were found to have higher performance than those who quit, who in turn were found to have higher performance than those who were fired (Wanous, Stumpf, & Bedrosian, 1979; Wells & Muchinsky, 1985).

Several criterion related problems have been discussed in the literature as they relate to the study of turnover.

In order to better understand the association between turnover and biodata, consideration of these issues is necessary.

Turnover Criterion Issues

Mobley, Griffeth, Hand, and Meglino (1979) found the bulk of individual-level turnover research centers on voluntary turnover. Likewise, Wells and Muchinsky (1985) in their study of performance and turnover found that involuntary separations were ignored as a topic of study. A related issue is the classification of voluntary turnover into functional and dysfunctional categories.

Voluntary versus Involuntary Turnover.

Lefkowitz and Katz (1969) found that the voluntary versus involuntary distinction of turnover has been largely overlooked. Campion (1991) examined the appropriateness of the dependent variable in turnover research and found it would be unreasonable to expect motivational models of turnover to predict turnover that reflected an organizational decision that it no longer wanted or needed an employee (i.e., involuntary turnover). Based on this analysis, Campion (1991) reported several measurement problems in turnover research.

First, in most studies it is unclear whether voluntary or involuntary turnover is being studied. Wanous, Stumpf, and Bedrosian (1979) stated that the fact that some have not separated voluntary from involuntary turnover may confound the dependent variable and may likely affect the relationship to predictor variables. The need to clarify the distinction between voluntary and involuntary turnover in future research was also expressed by Forrest, Cummings, and Johnson (1977).

Second, the use of tenure as a substitute measure of turnover (Campion, 1991) is questionable. For example, the definitions for long and short tenure have varied greatly (e.g. long tenure has varied from ten months to thirteen years). The comparison of long and short tenure employees is somewhat different from comparing those who turnover from those who stay.

A third measurement problem voiced by Campion (1991) is the accuracy of turnover data. The classification of turnover as voluntary or involuntary may be somewhat ambiguous and may contain an unknown amount of measurement error. In addition, personnel records that allow only a single reason for separation (e.g., employee disliked their supervisor or the hours worked, but found a better paying position) may make measurement arbitrary. In addition, overused general classification categories (e.g., personal reasons) may also be inadequate. Some have also classified the same reasons for turnover differently. For example, pregnancy was classified by Marsh and Mannari (as cited in Mobley et al., 1979) and Campion (1991) as voluntary turnover in contrast to Mirvis and Lawler (1977) and Waters, Roach, and Waters (1976) who classified it as involuntary. Lefkowitz and Katz (1969) found that reasons recorded for turnover at time of separation do not always agree with reasons given at a later point in time.

Additional research found voluntary and involuntary leavers to vary on factors such as performance and job attitudes. Wild (1979) generally found employees who left voluntarily to be less satisfied than those who left involuntarily. In fact, eighty percent of dissatisfied leavers left voluntarily while sixty-four percent of satisfied leavers left involuntarily.

Wanous, Stumpf, and Bedrosian (1979), in a study of job survival among new employees, found job performance to be a stronger predictor of involuntary turnover than job attitudes (e.g., job satisfaction). Employees who left voluntarily had higher performance, but less favorable job attitudes. Conversely, involuntary leavers had more favorable job attitudes and lower performance.

Stumpf and Dawley (1981) also found a negative relationship between performance and turnover. This relationship was greater for involuntary than for voluntary turnover. Upon further analysis, Stumpf and Dawley (1981) found two discriminant functions which differentiated those employed, those who left voluntarily, and those who turnover involuntarily. The first function distinguished those employed from all those who turned over. Turnover was greatest for males, with poor attendance, poor performance, and few merit increases. The second function compared tellers who left involuntarily to those leaving voluntarily. Biodata that differentiated voluntary from involuntary turnover included sex, age, education, tenure, and absenteeism. Younger, female, more educated, less tenured, and less frequently absent tellers were more likely to leave voluntarily than involuntarily.

Biodata items as well as performance ratings also separated voluntary from involuntary turnover in a study of managers (Wells & Muchinsky, 1985). In this study promoted employees were compared to those who were fired (i.e., left involuntarily) and those who quit (i.e., left voluntarily). Significantly more males left involuntarily than voluntarily. Single employees were more likely to be either fired or have quit than to have been promoted. In addition, significantly more minorities quit than were fired or who were promoted. Managers who were promoted had higher levels of performance than those who quit, who in turn performed better than those who were fired.

Finally, a meta-analysis of the relationship between performance and turnover, which examined both voluntary and involuntary turnover (McEvoy & Casico, 1987), found a significantly negative relationship between performance and turnover (-.28). This relationship was stronger for involuntary turnover than for all turnover or voluntary turnover. In sum, as might be expected, individuals with lower performance are more likely to leave involuntarily than voluntarily. In addition, some biodata items (e.g., gender, marital status, education, tenure) have also differentiated voluntary from involuntary turnover. A supplemental method of classifying the types of turnover has been offered by Porter and Steers (1973) in order to better understand the process and ways to address the different types of turnover.

Effective versus Ineffective Leavers.

Porter and Steers (1973) suggested that future research efforts should make a clear distinction between effective and ineffective leavers. This recommendation directly questions the assumption that the reduction of all turnover is desirable. At least a portion of those who turnover may be effective. Departure of ineffective employees would make positions available for presumably better performers. If, on the other hand, those with a very high degree of independence, self-confidence, aggressiveness, and high career aspirations do leave more often, as reported by Porter and Steers (1973), and if these persons are better performers, then it may be essential for organizations to tolerate certain levels of turnover in exchange for increased efficiency and productivity while these employees are there.

Functional versus Dysfunctional Turnover.

Dalton, Krackhardt, and Porter (1981) also questioned the fundamental assumption that all turnover is dysfunctional. Suggested instead is a taxonomy that subdivides voluntary turnover based on the organization's evaluation of the employee into functional and dysfunctional groupings. Functional turnover occurs when "the individual wants to leave the organization, but the organization is unconcerned. The organization has a negative evaluation of the individual". Functional turnover is beneficial to the organization. Conversely, dysfunctional turnover occurs when "the individual wants to leave the organization, but the organization prefers to retain the individual." The key is that if functional and dysfunctional turnover are combined the impact of turnover on the organization is overstated (i.e., the benefits of functional turnover are ignored).

As an illustration, Dalton et al. (1981) found the turnover of bank tellers in his study was thirty-two percent. Once the low-quality employees were subtracted, the dysfunctional turnover was only eighteen percent, and half of those employees were determined to be easily replaceable. Removing these employees reduced the amount of dysfunctional turnover to only nine percent. Of the dysfunctional turnover reported by Dalton et al., between forty-five and fifty-two percent was considered unavoidable or out of the control of the organization (e.g., education, family commitments, health matters).

Similarly, based on his review of the literature, Campion (1991) suggested three refinements to the concept of turnover consequences. The first refinement, as mentioned above by Dalton et al. (1981), was to acknowledge that organizations feel unable to do anything about some turnover (i.e., unavoidable turnover). Losing employees for avoidable reasons may be positive for the organization if it could have averted the turnover and elected not to intervene (e.g., employee demanded too large of a wage increase, the employee's performance was substandard, the change in the working conditions demanded were too expensive). On the other hand, unavoidable turnover is generally considered negative by the organization (e.g., death, mid-career change, spouse relocation).

The second refinement, also mentioned earlier, is the determination of whether turnover is functional or dysfunctional to the organization. The functionality of turnover can be ascertained by determining if an employee was a poor performer, if the organization would be reluctant to rehire the individual, and if the employee can be easily replaced. Again, only dysfunctional turnover is considered bad for the organization.

The third refinement deals with the utility of former employees and potential replacement employees (i.e., productivity of former versus replacement, cost differences between former and replacement, transaction costs). Turnover is considered favorable if the transaction results in more productive employees or if higher paid employees are replaced with lower paid ones. Positive utility can also occur when a combination of cost and performance are considered (e.g., exchanging a good performer for one that is more moderate, but at a much lower salary or benefit level).

In summary, the basic rationale for utilizing biodata as a predictor variable is that it reflects a cycle of choice, development, and adaptation which has evolved over time and should allow prediction of future behavior. The sole defining characteristic of biodata is that it reflects a part of one's current or past life history.

The literature has revealed support for the prediction of turnover utilizing numerous biodata variables. Tenure, family responsibility, vocational interest, previous experience, and emotional stability have shown a negative relationship to turnover while age, gender, education, and intelligence have displayed an inconclusive or very limited relationship to turnover. Personality variables such as independence, self-confidence, and aggressiveness have shown a positive relationship to turnover.

The relationship between job performance and turnover also received attention in the literature. Generally, performance has shown a negative relationship with turnover. In addition, biodata items have been used to predict job performance with mean validities ranging from .28 to .50.

The literature revealed three turnover criterion issues which merit attention when conducting turnover research. These are the voluntary versus involuntary turnover distinction, the effectiveness versus ineffectiveness of those who leave, and whether turnover was functional or dysfunctional to the organization.

General Statement of Hypotheses

Hypothesis #1

Biodata items will be related to turnover. This hypothesis is a replication of previous research and, as noted above, some biodata items have shown a more clear relationship to turnover than others. For example, biodata items such as level of family responsibility, previous experience, level of interest (measured by dimensions on interest inventories which are related to one's job), and possibly age have shown a negative relationship to turnover. Other biodata such as sex, level of education, and intelligence have shown a less clear relationship to turnover. Extreme personality characteristics have also been linked to higher levels of turnover (Porter & Steers, 1973).

Hypothesis #2

Biodata items will differentiate between employees who leave for voluntary versus involuntary reasons. As noted earlier, limited previous research found voluntary and involuntary leavers to differ on age, sex, education level, and tenure. According to Stumpf and Dawley (1981), involuntary leavers were more likely to be older, male, less educated, and have more tenure.

Hypothesis #3

Voluntary leavers will have higher performance evaluations than involuntary leavers. This hypothesis, which is related to the second hypothesis, examines the relationship between performance and type of turnover and is based on the findings of McEvoy and Casico (1987), Stumpf and Dawley (1981), Wanous, Stumpf, and Bedrosian (1979), and Wells and Muchinsky (1985) who found voluntary leavers to have higher levels of performance than involuntary leavers.

Hypothesis #4

Functional and dysfunctional leavers will differ on biodata items. This hypothesis is based on the expanded taxonomy of voluntary turnover by Dalton and Krackhardt (1981) and Campion (1991). The expanded taxonomy breaks voluntary turnover into functional and dysfunctional turnover. Rothstein, Schimdt, Erwin, Owen, and Sparks (1990) have found several biodata items which are positively related to performance (e.g., education level, age, similar experience). While there is no clear, if any, previous research that explores this relationship, it is proposed that dysfunctional leavers will have higher levels of traits (as measured by biodata items) that are related to higher performance and effectiveness (e.g., education level or age as suggested by Rothstein et al., 1990, or as a measure of personality traits such as aggressiveness as suggested by Porter and Steers, 1973) than functional leavers.

Method

Subjects

The data base consisted of 958 former and current production employees of a plastic injection molding facility located in the mid Southern United States. All subjects began working for the company between October of 1981 and September of 1995.

Procedure

Archival data for each subject were collected from personnel files. Biodata items were collected from each subject in order to generate twenty-six predictor variables (see Table 1). These items include distance current and previous residence are from work as indicated by the zip code (zip code was used as a proxy for distance), age, gender, years of education, total months of work experience, months of work experience in a similar industry or position,

Table 1
PREDICTOR VARIABLES

CURRENT DISTANCE - Distance residence is from plant
1 = less than 5 miles
2 = 6-20 miles
3 = greater than 20 miles

PREVIOUS DISTANCE - Distance previous residence from plant
1 = less than 10 miles
2 = 11 to 60 miles
3 = greater than 60 miles

AGE - Age of employee at time of application

SEX - Gender of subject

EDUCATION - Years of education

TOTAL EXPERIENCE - Total months of work experience

DURATION - Months on last job

SIMILAR EXPERIENCE - Months of related work experience

EMPLOYMENT STATUS - Whether employed or unemployed at hire

FAMILY RESPONSIBILITY - Combination of marital status and number of dependents.

REFERRED - Method of employment contact

TENURE - Length of service

START WAGE - Starting rate of pay

WONDERLIC - Score on Wonderlic Personnel Test

PROFILE SCALES

Aptitudes measured:

MENTAL ALERTNESS	**BUSINESS TERMS**
MEMORY RECALL	**VOCABULARY**
PERCEPTION	**MECHANICAL INTEREST**

Personality dimensions measured:

NERVOUS TENSION	**DOMINANCE**
COMPETITIVENESS	**EMOTIONAL MATURITY**
WORK MOTIVATION	**SOCIABILITY**

months on most recent job, employment status at time of hire (i.e., employed or unemployed), level of family responsibility (determined from marital status and number of dependents), method of referral (e.g., another employee, state employment service), tenure (as generated from date of hire and date of separation), shift worked at hire, starting wage rate (used as proxy for skill level of position only), Wonderlic Personnel Test score, and scores on the Personal Evaluation Program published by Profiles International, Inc.(eighteen sub-tests).

The first six sub-tests of the Profile scales purport to measure mental aptitudes which include mental alertness, business terms, memory recall, vocabulary, perception, and mechanical interest. The next ten sub-tests were designed to measure personality dimensions. These dimensions include nervous tension, character strength, work habits, sociability, emotional maturity, dominance, competitiveness, stamina, naiveté, and work motivation. Based on past research six of the ten personality dimensions were utilized to predict criterion variables (Porter & Steers, 1973; Schuh, 1967a).

Porter and Steers (1973) report that those who leave have higher levels of achievement orientation, aggression, ascendance, sociability, anxiety, and neuroticism. Based on the similarity of construct descriptions, these traits were found to be comparable to those measured by the Profile scales Work Motivation, Competitiveness, Dominance, Sociability, and Nervous Tension. In addition, those who stay were found to exhibit higher emotional stability and maturity which resembles Emotional Maturity from the Profile, as well as more moderate levels of achievement orientation which coincided with the Competitiveness scale. These traits were also found to be comparable to Profile scales based on construct descriptions.

Scores on the personality dimension competitiveness were divided into two groups to compare high versus moderate scores. Scores that fell in the top two stanines were categorized as high while those that fell in stanine five were classified as moderate.

Scores on the remaining personality dimensions (work motivation, dominance, sociability, nervous tension, and emotional maturity) were used as continuous variables because the literature specific to these traits indicates that turnover was related to high levels of work motivation, dominance, sociability, and nervous tension and low levels of emotional maturity.

Similarly, scores on the Profile scale measuring mechanical interest were also used as continuous variables because those with higher levels of job interest have been shown to be less likely to turnover (Porter & Steers, 1973; Schuh, 1967a; Kriedt & Gadel, 1953). All production positions require some mechanical ability, and this need increases as employee progress in job grade.

The Reliability and Validity Manual for the Profile sub-tests reports split-half reliability estimates for the six mental aptitudes which ranged from .64 to .89. In addition, split-half reliabilities for the ten personality dimensions ranged from .45 to .74.

The current and previous residence distance from work was calculated from the average distance the center of the geographic area [as represented by the zip code] was from the plant. Zip codes for distance of current residence were assigned a value from one to three according to the number of miles between the plant and that zip code area (i.e., 1 = up to five miles, 2= six to twenty, 3 = greater than twenty miles). These distances defined whether the employee lived near the plant, within a moderate commute, or if a long commute was necessary.

Similarly, the zip code of the previous residence was also used as a measure of the number of miles between the plant and previous residence. These values (see Table 1) indicated if relocation was not an issue (less than 10 miles), an issue but not necessary (eleven to sixty miles), or if relocation was very likely (more than sixty miles).

As discussed by Porter and Steers (1973), the level of family responsibility was determined from a combination of marital status and number of dependents. Employees were determined to have a high level of family responsibility if married and at least one dependent and a low level of family responsibility if single and no dependents.

Eight criterion variables were collected from personnel files (see Table 2). These variables included performance review scores, voluntariness of separation recorded by the human resource manager (as used by Campion, 1991, to designate if employees were terminated by the company or elected to leave on their own), reason for leaving, indication of ninety-day training completion, and functionality of voluntary separations.

Employees receive performance reviews at thirty-day intervals during the ninety-day training period and approximately every sixty days following training.

Table 2
CRITERION VARIABLES

REVIEW1 - First performance evaluation
REVIEW2 - Second performance evaluation
REVIEW3 - Third performance evaluation
LAST REVIEW - Last performance evaluation
VOLUNTARINESS - Whether employee left willingly or was dismissed
SEPARATION - Reason for separation (one of ten)

Voluntary Reasons
1. Quit without reason
2. Quit for better job
3. Quit to return to school
4. Quit, disliked shift assignment
5. Quit, disliked actual work involved

Involuntary Reasons
1. Terminated for poor performance
2. Terminated for poor attendance
3. Terminated not for performance/attendance

Other Reasons
1. Laid-off
2. Medical reasons

NINETY DAY T/O - Whether employee completed training period
FUNCTIONALITY - Whether voluntary separation was beneficial

Functional - Voluntary separation that company views as positive to the organization.
Dysfunctional - An employee leaves voluntarily who the company wishes to retain.

Performance scores completed by direct supervisors were collected for the first, second, third, and last performance reviews. Scores on these reviews can range from six to thirty with seventeen designated by the organization as the cutoff for satisfactory performance.

In order to most accurately measure reason for leaving and prevent over use of general classifications, ten reasons for leaving were used. Two of these reasons were deemed unavoidable and not used in further analysis (see Table 2).

Turnover prior to completion of the ninety-day training period was coded by examining employee tenure. Those with less than ninety days of tenure were considered to have not completed training (i.e., turned-over), and those with ninety or more days of tenure were coded as having finished the training before leaving (i.e., not having turned-over).

The voluntariness of separation was determined by examining reason for leaving. Voluntary reasons included quit without a reason given, quit for a better job, quit to return to school, quit because of dislike for the shift hours, and quit because of dislike for the actual work involved. Involuntary reasons included terminated for poor performance, terminated for poor attendance, and terminated for reasons other than performance or attendance. Employees who were laid off and did not return to work or who left because of medical reasons (e.g., pregnancy) were excluded from the study because the reason for leaving is out of their control at the time of separation. For example, in the case of a layoff, the employee does not choose to leave and the organization has not determined that their performance is unacceptable or that a policy violation has occurred. Likewise, when employees leaves for a medical reason (e.g., pregnancy) they could not stay if they wanted and the organization has not determined that their conduct justifies discharge.

Finally, the functionality of voluntary leavers was determined by the level of performance recorded on the last review and the ease of replacement of the employee (Dalton et al., 1981). Departed employees with an unsatisfactory last review (i.e., performance review scores below seventeen) were considered as functional leavers unless hired into a skilled position or if the employee had completed the ninety-day training period. Those at or above seventeen on their last review and those who had worked more than ninety days or who were hired into higher skilled positions (e.g., maintenance technicians, tool makers) are considered more difficult to replace and, therefore, were considered as dysfunctional leavers. Starting wage rate was used to determine the level of skill (i.e., unskilled or more than unskilled) of the position an employee began working in. Employees starting at six dollars or less were classified into general labor positions while those starting above that point were hired into more skilled positions. It should be noted that no employee hired into an unskilled position started above six dollars per hour. In addition, all employees hired into more than unskilled positions started above six dollars per hour.

Data Analysis and Results

Table 3 displays descriptive statistics for variables in the study. In addition, the appendix contains a correlation matrix of all variables.

In order to ensure the accuracy of the data, cases were scanned for internal consistency. This process included verifying that responses to variables such as age and education, date of hire and date of termination, and length of total experience and length of similar experience were logical. For example, it would be impossible to have more months of similar experience than months of total experience. This analysis found that responses to biodata items were highly logical and that inconsistent data was not a problem.

Hypothesis #1

The first hypothesis, that biodata items are related to turnover, was tested utilizing logistic regression. Norusis (1992) states that in logistic regression statistical models are built to estimate the probability of an event occurring

Table 3
Descriptive Statistics

Variable	Mean	Std Dev	Minimum	Maximum	N	Label
ZIP	42384.07	690.10	40111	47715	955	Zip Code
PREVZIP	43711.44	9111.24	9565	97501	425	Previous Zip Code
AGE	25.61	7.60	18	57	570	Age
SEX	.63	.48	0	1	957	Gender
EDUCAT	12.58	1.12	2	18	958	Education in Years
WORKEXP	43.26	43.67	0	429	944	Work Experience in M
DURATION	15.20	22.70	0	248	947	Duration of Last Job
SIMEXPER	7.13	20.93	0	192	949	Related Work Experie
EMPSTAT	.32	.47	0	1	956	Employment Status
MARTIAL	.31	.46	0	1	948	Martial Status
DEPENDS	.66	1.05	0	5	949	Number of Dependents
REFERRED	2.37	1.21	1	4	736	Referred By
SMON	6.44	3.00	1	12	957	Start Month
SDAY	16.47	8.81	1	31	957	Start Day
SYEAR	90.71	3.47	81	95	956	Start Year
TMON	7.18	3.04	1	12	892	Termination Month
TDAY	17.35	9.24	1	31	892	Termination Day
TYEAR	91.76	3.05	83	95	893	Termination Year
REASON	3.53	2.63	1	8	798	Reason for Leaving
SHIFT	1.78	.96	1	5	920	Shift
STARTRAT	4.52	.73	3.50	7.50	764	Start Rate
WONDRLIC	21.10	5.03	3	41	887	Wonderlic
PRO1	26.92	4.74	4	39	572	Mental Alertness
PRO2	5.04	1.79	0	12	572	Business Terms
PRO3	5.61	2.32	0	11	572	Memory Recall
PRO4	33.62	5.32	3	49	572	Vocabulary
PRO5	17.65	3.61	0	47	572	Perception
PRO6	8.32	3.06	0	17	567	Mechanical Interest
PRO7	11.15	2.72	4	16	567	Nervous Tension
PRO10	8.88	3.45	0	16	568	Sociability
PRO11	7.34	2.96	0	16	567	Emotional Maturity
PRO12	6.45	2.89	0	14	567	Dominance
PRO13	10.48	2.96	2	16	568	Competitiveness
PRO16	4.97	2.36	0	12	567	Work Motivation
REVIEW1	17.52	1.36	10.0	25.0	501	First Review
REVIEW2	18.03	1.46	13.0	25.0	357	Second Review
REVIEW3	18.30	1.67	12.0	25.0	289	Third Review
LASTREV	18.00	2.20	10.0	25.0	519	Last Review
CUREMP	.10	.30	0	1	958	Current Employee
VOLNESS	.66	.47	.00	1.00	702	Type of Turnover

Table 3 continued
Descriptive Statistics

Variable	Mean	Std Dev	Minimum	Maximum	N	Label
TENURE	272.99	599.51	.00	3882.00	881	Length of Service
FUNALITY	.42	.50	.00	1.00	198	Functionaity
CURADD	1.35	.61	1.00	3.00	954	Current Address
PREADD	1.46	.73	1.00	3.00	421	Previous Address
EMPS	.24	.43	.00	1.00	736	Referral Status
OFFSHIFT	.51	.50	.00	1.00	920	Off Shift
COMPETE	1.77	.42	1.00	2.00	181	Competitiveness Stan
NINETO	.65	.48	.00	1.00	881	Ninety-day Turnover
FAMRES	.28	.45	.00	1.00	676	Family Responsible

or not occurring. Several multivariate statistical techniques can be used to predict whether an event will occur. However, when the dependent variable can have only two values (i.e., an event occurring or not occurring) the assumptions necessary (e.g., normal distribution of errors) for multiple regression are violated. Group membership can be predicted with linear discriminant analysis; however, in order for prediction to be ideal, multivariate normality of independent variables and equal variance-covariance matrices in the two groups are needed. The logistic regression model demands meeting far fewer assumptions than discriminant analysis, and it performs well even when required assumptions for discriminant analysis are satisfied. This conclusion is consistent with the findings of Press and

Wilson (1978) who found that one advantage of using logistic regression is that it is relatively robust and preferable in situations when assumptions of normality are violated. This finding is especially true when independent variables are dichotomous or qualitative.

In this analysis, logistic regression was used to identify the prediction model for which employees will turnover before completing their ninety-day training period and those who will stay long enough to complete training. Subjects with an estimated probability of leaving before completion of the ninety-day training period greater than .5 were predicted to turnover, while those with an estimated probability of leaving less than .5 were predicted to not turnover. The goodness of fit or significance of the resulting model was assessed with the chi-square statistic and by examining the classification table of predicted versus observed events. The model chi-square statistic tests the null hypothesis that the coefficients for all terms in the resulting model, excluding the constant, are zero. In logistic regression, the logistic regression coefficients associated with each independent variable (i.e., biodata item) are interpreted as the change in the log odds associated with a unit change in the independent variables. The direction of the effect of each coefficient can be interpreted by the sign of the coefficient. For example, as the value of an independent variable with a positive coefficient increases, the probability of the event occurring also increases.

In a discussion of procedures to select predictors, Stevens (1986) suggests selecting a small set of predictors in order to find an equation that will cross-validate well. Stevens states that predictors that are supported by previous research should be forced into the equation first. Additional predictors should then be entered and checked for their incremental value.

Based on past research age, family responsibility, similar experience, mechanical interest, nervous tension, sociability, emotional maturity, dominance, competitiveness, and work motivation were entered initially using forced entry. The remaining variables were examined for entry using forward stepwise selection.

The significance of each biodata item in the initial model was assessed by examining the Wald statistic which tests the null hypothesis that the corresponding coefficient was zero. The literature reveals that those who turnover are more likely than those who stay to be younger, have less family responsibility, less experience, lower job interest; higher work motivation, dominance, sociability, and nervous tension scores, lower emotional maturity; and higher as opposed to moderate competitiveness. Wald statistics for the coefficient for age, family responsibility, previous experience, level of interest, emotional maturity were, therefore, predicted be negative. The coefficients for work motivation, dominance, sociability, nervous tension, and competitiveness were predicted to be positive.

The expected relationships between the remaining biodata items and turnover are less predictable and were included on an exploratory basis. The goodness of fit of the equation resulting from forward stepwise selection was assessed by examining the model chi-square statistic. The model chi-square of the initial model and the model resulting from forward stepwise selection were used to compare incremental differences in the goodness of fit of each model.

Results Hypothesis #1.

The results of the logistic regression of ninety-day turnover on biodata variables are displayed in Tables 4a, 4b, 4c, 4d, 4e, and 4f. The chi-square for the model with all ten predictors reported in the literature to be related to turnover (x^2=18.645; df=10,52; p=.0450) indicates that it does predict who will turnover prior to completing training (Table 4a). However, when all predictors are included in the model the sample size is reduced due to listwise deletion of cases which limits the degrees of freedom and the power of the resulting model. This model has a subject to predictor ratio of just over five to one. Stevens (1986) has suggested a subject to predictor ratio of at least fifteen to one in order for regression equations to cross-validate well.

With this in mind, competitiveness, the scale for which there was the most missing data, was removed from the analysis. The revised model resulted in a sufficient sample to predictor ratio; however, the model chi-square(x^2=9.078; df=9, 141; p=.4301) indicates that it does not predict turnover (Table 4b). In addition, none of the Wald Statistics for the predictors in the equation was significant indicating that none of the coefficients is different from zero.

In light of the fact that the model as a whole was not significant, the bivariate relationships between turnover and each of the ten biodata items in the model was examined.

Table 4a
Logistic Regression Analysis: 90 Day Turnover

Initial Model with all variables

	Chi-Square	df	Significance
-2 Log Likelihood	39.838	41	.5222
Model Chi-Square	18.645	10	.0450
Improvement	18.645	10	.0450
Goodness of Fit	39.036	41	.5582

		Predicted Worked more than 0	Predicted Worked less than 1	%Correct
Observed				
Worked more than	0	35	4	89.74%
Worked less than	1	7	6	46.15%
			Overall	78.85%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-1.5151	1.4049	1.1630	1	.2808	.0000	.2198
SIMEXPER	-.0030	.0266	.0128	1	.9100	.0000	.9970
AGE	-.1651	.1507	1.2003	1	.2733	.0000	.8478
MECH INT	.1694	.2004	.7144	1	.3980	.0000	1.1846
NERV TENSION	.1985	.1779	1.2448	1	.2646	.0000	1.2195
SOCIABLE	-.4283	.2057	4.3332	1	.0374	-.1997	.6516
EMOT MATURITY	.0294	.1701	.0299	1	.8627	.0000	1.0298
DOMINANCE	.0414	.1699	.0594	1	.8075	.0000	1.0423
COMPETE	.0202	1.4338	.0002	1	.9888	.0000	1.0204
WORK MOT	.5864	.2772	4.4758	1	.0344	.2058	1.7975
Constant	-.7561	5.4911	.0190	1	.8905		

This analysis revealed two variables that predicted turnover when all other predictors were removed. First, a logistic regression analysis of turnover on age was significant (χ^2=4.356; df=1,547; p=.0369; B=-.0247) indicating that older employees were less likely to turnover than relatively younger ones.

The second variable related to turnover is family responsibility. A logistic regression analysis of turnover on family responsibility resulted in a significantly

Table 4b

Logistic Regression Analysis: 90 Day Turnover

Revised Model without Competitiveness

	Chi-Square	df	Significance
-2 Log Likelihood	153.231	131	.0896
Model Chi-Square	9.078	9	.4301
Improvement	9.078	9	.4301
Goodness of Fit	147.364	131	.1556

		Predicted Worked more than	Predicted Worked less than	
Observed		0	1	%Correct
Worked more than	0	103	1	99.04%
Worked less than	1	33	4	10.81%
			Overall	75.89%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.2732	.5131	.2836	1	.5944	.0000	.7609
SIMEXPER	.0061	.0065	.8768	1	.3491	.0000	1.0061
AGE	-.0326	.0436	.5576	1	.4552	.0000	.9680
MECH INT	.0530	.0704	.5672	1	.4514	.0000	1.0544
NERV TENSION	.0144	.0803	.0321	1	.8578	.0000	1.0145
SOCIABLE	.0563	.0672	.7010	1	.4024	.0000	1.0579
EMOT MATURITY	-.0811	.0710	1.3073	1	.2529	.0000	.9221
DOMINANCE	-.1201	.0699	2.9485	1	.0860	-.0764	.8869
WORK MOT	.0165	.0985	.0280	1	.8672	.0000	1.0166
Constant	-.0914	1.6573	.0030	1	.9560		

negative relationship between family responsibility and turnover (χ^2=4.363; df=1,624; p=.0367; B=-.3832). This finding indicates that employees with more family responsibility are less likely to turnover.

In subsequent analyses, variables that neither contributed to the omnibus model nor evinced significant bivariate relationships with turnover (i.e., personality items, similar experience, mechanical interest) were excluded. This step was done in order to preserve sufficient degrees of freedom to meaningfully explore the relationship between turnover and additional biodata items which in the literature were not mentioned or lacked consistent findings.

Table 4c contains the logistic regression analysis of ninety-day turnover on family responsibility and age, the two variables predicted by previous research to be related to turnover and found related to turnover in the present research. The model chi-square for this model (χ^2=14.556; df=2,391; p=.0007) indicates that it does predict who will turnover prior to completing training.

Next, exploratory predictor variables were added to the model. Table 4d contains the logistic regression of ninety-day turnover on family responsibility, age, and fourteen exploratory variables. Exploratory variables included Wonderlic scores, employment status, duration on last job, distance of previous address from plant, distance of current address from plant, gender, education level, months of work experience, referral method, and five aptitude scales; mental alertness, knowledge of business terms, memory recall, vocabulary, and perception. As stated earlier, exploratory variables were allowed to enter the model through forward stepwise selection.

Table 4c
Logistic Regression Analysis: 90 Day Turnover with Family Responsibility and Age

Model with Family Responsibility and Age

	Chi-Square	df	Significance
-2 Log Likelihood	508.859	388	.0000
Model Chi-Square	14.556	2	.0007
Improvement	14.556	2	.0007
Goodness of Fit	390.637	388	.4529

Classification Table for NINETO

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	37	116	24.18%
Worked less than	1	27	211	88.66%
			Overall	63.43%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.5465	.2529	4.6713	1	.0307	-.0714	.5790
AGE	-.0361	.0163	4.8705	1	.0273	-.0741	.9646
Constant	1.4740	.4023	13.4206	1	.0002		

The initial model that resulted contains age and family responsibility, which were forced into the model first. Employment status and distance of previous address were added on successive steps. The chi-square for the resulting model containing four predictors (χ^2=11.072; df=2,62; p=.0039) indicates that it does predict who will turnover prior to completing training. However, the sample size was again limited due to listwise deletion of cases restricting the power of the model. With four predictors and sixty-two

Table 4d
Logistic Regression Analysis: 90 Day Turnover with Family Responsibility, Age, and Exploratory Variables

Initial Model with Family Responsibility and Age

	Chi-Square	df	Significance
-2 Log Likelihood	68.254	59	.1917
Model Chi-Square	.355	2	.8374
Improvement	.355	2	.8374
Goodness of Fit	62.031	59	.3686

Classification Table for NINETO

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	47	0	100.00%
Worked less than	1	15	0	.00%
			Overall	75.81%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.0929	.6728	.0191	1	.8902	.0000	.9113
AGE	-.0222	.0466	.2270	1	.6338	.0000	.9781
Constant	-.5043	1.2248	.1695	1	.6805		

Model with Family Responsibility, Age, and Employment Status

	Chi-Square	df	Significance
-2 Log Likelihood	61.608	58	.3483
Model Chi-Square	6.646	1	.0099
Improvement	6.646	1	.0099
Goodness of Fit	64.529	58	.2591

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	47	0	100.00%
Worked less than	1	15	0	.00%
			Overall	75.81%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	.0526	.7185	.0054	1	.9416	.0000	1.0540
AGE	-.0431	.0477	.8189	1	.3655	.0000	.9578
EMPSTAT	-1.8581	.8265	5.0547	1	.0246	-.2116	.1560
Constant	.5416	1.2867	.1772	1	.6738		

Table 4d continued
Logistic Regression Analysis: 90 Day Turnover with Family Responsibility, Age, and Exploratory Variables

Model with Family Responsibility, Age, Employment Status, and Previous Address

	Chi-Square	df	Significance
-2 Log Likelihood	57.183	57	.4683
Model Chi-Square	11.072	2	.0039
Improvement	4.425	1	.0354
Goodness of Fit	54.027	57	.5873

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	42	5	89.36%
Worked less than	1	10	5	33.33%
			Overall	75.81%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	.0666	.7807	.0073	1	.9320	.0000	1.0688
AGE	-.0296	.0494	.3601	1	.5484	.0000	.9708
EMPSTAT	-1.9181	.8615	4.9578	1	.0260	-.2082	.1469
PREADD	1.0495	.5124	4.1960	1	.0405	.1794	2.8564
Constant	-1.3215	1.5915	.6895	1	.4063		

cases the subject to predictor ratio was at the lower acceptable limit of fifteen to one.

With this in mind, the fourteen exploratory variables were examined for substantial missing data. The distance of previous address and the five aptitude scales were found to contain substantial missing data. While fifty-six percent of the cases were missing the previous address variable, the bivariate relationship between previous address and turnover was significant (χ^2=19.314; df=1,390; p=.0000) and, thus, not excluded from additional analyses. However, the five aptitude scales were excluded from further analyses because all were missing data from forty-one percent of the cases and the bivariate relationships between these variables and turnover were not significant.

Table 4e contains the results from the revised logistic regression analysis of ninety-day turnover on family responsibility, age, and exploratory variables (the five aptitude scales were removed due to missing data).

The initial model, which resulted from the revised analysis, again contains age and family responsibility which were forced into the model. Employment status, distance of previous address, and months of work experience were added on successive steps. The chi-square for the resulting model which contained five predictors (χ^2=32.235; df=3,125; p=.0000) indicates that it does predict who will turnover prior to completing training.

However, examination of the Wald statistic for the logistic regression coefficient for family responsibility in Table 4e indicates that it is not different from zero (Wald=.1033, p=.7479). In order to generate a more parsimonious model the analysis was run again without family responsibility (see Table 4f). Age was again forced into

Table 4e

Revised Logistic Regression Analysis: 90 Day Turnover with Family Responsibility, Age, and Exploratory Variables

Initial Model with Family Responsibility and Age

	Chi-Square	df	Significance
-2 Log Likelihood	168.720	122	.0033
Model Chi-Square	4.366	2	.1127
Improvement	4.366	2	.1127
Goodness of Fit	125.002	122	.4078

Classification Table for NINETO

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	24	36	40.00%
Worked less than	1	18	47	72.31%
			Overall	56.80%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.1590	.4151	.1467	1	.7017	.0000	.8530
AGE	-.0501	.0288	3.0276	1	.0819	-.0770	.9511
Constant	1.4468	.7418	3.8043	1	.0511		

Model with Family Responsibility, Age, and Employment Status

	Chi-Square	df	Significance
-2 Log Likelihood	153.956	121	.0231
Model Chi-Square	14.764	1	.0001
Improvement	14.764	1	.0001
Goodness of Fit	126.852	121	.3398

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	38	22	63.33%
Worked less than	1	15	50	76.92%
			Overall	70.40%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.0618	.4432	.0194	1	.8891	.0000	.9401
AGE	-.0658	.0298	4.8823	1	.0271	-.1307	.9363
EMPSTAT	-1.5600	.4252	13.4606	1	.0002	-.2606	.2101
Constant	2.3391	.8069	8.4026	1	.0037		

Table 4e continued

Revised Logistic Regression Analysis: 90 Day Turnover with Family Responsibility, Age, and Exploratory Variables

Model with Family Responsibility, Age, Employment Status, and Previous Address

	Chi-Square	df	Significance
-2 Log Likelihood	143.915	120	.0676
Model Chi-Square	24.805	2	.0000
Improvement	10.041	1	.0015
Goodness of Fit	127.056	120	.3122

Classification Table - NINETO

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	40	20	66.67%
Worked less than	1	13	52	80.00%
			Overall	73.60%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.0024	.4776	.0000	1	.9961	.0000	.9977
AGE	-.0569	.0312	3.3290	1	.0681	-.0888	.9446
EMPSTAT	-1.6504	.4528	13.2875	1	.0003	-.2587	.1920
PREADD	.8989	.3059	8.6359	1	.0033	.1983	2.4570
Constant	.8016	.9519	.7092	1	.3997		

Model with Family Responsibility, Age, Employment Status, Previous Address, and Work Experience

	Chi-Square	df	Significance
-2 Log Likelihood	136.485	119	.1303
Model Chi-Square	32.235	3	.0000
Improvement	7.429	1	.0064
Goodness of Fit	121.077	119	.4297

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	39	21	65.00%
Worked less than	1	14	51	78.46%
			Overall	72.00%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
FAMRES	-.1601	.4980	.1033	1	.7479	.0000	.8521
AGE	-.1125	.0410	7.5475	1	.0060	-.1813	.8936
EMPSTAT	-1.8522	.4773	15.0604	1	.0001	-.2782	.1569
PREADD	.8413	.3056	7.5789	1	.0059	.1818	2.3194
WORKEXP	.0161	.0062	6.7807	1	.0092	.1683	1.0162
Constant	1.6356	1.0609	2.3769	1	.1231		

the model first followed by employment status, previous address, and work experience which were entered through forward stepwise selection on successive steps. The chi-

Table 4f

Revised Logistic Regression Analysis: 90 Day Turnover with Age, and Exploratory Variables

Initial Model with Age

	Chi-Square	df	Significance
-2 Log Likelihood	236.277	173	.0010
Model Chi-Square	3.799	1	.0513
Improvement	3.799	1	.0513
Goodness of Fit	174.923	173	.4448

Classification Table for NINETO

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	16	61	20.78%
Worked less than	1	15	83	84.69%
			Overall	56.57%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
AGE	-.0427	.0222	3.6858	1	.0549	-.0838	.9582
Constant	1.3806	.6133	5.0681	1	.0244		

Model with Family Age and Employment Status

	Chi-Square	df	Significance
-2 Log Likelihood	220.176	172	.0077
Model Chi-Square	16.101	1	.0001
Improvement	16.101	1	.0001
Goodness of Fit	174.904	172	.4240

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	42	35	54.55%
Worked less than	1	24	74	75.51%
			Overall	66.29%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
AGE	-.0561	.0231	5.8927	1	.0152	-.1284	.9454
EMPSTAT	-1.3622	.3501	15.1414	1	.0001	-.2358	.2561
Constant	2.1908	.6731	10.5935	1	.0011		

Table 4f continued
Revised Logistic Regression Analysis: 90 Day Turnover with Age and Exploratory Variables

Model with Age, Employment Status, and Previous Address

	Chi-Square	df	Significance
-2 Log Likelihood	209.069	171	.0251
Model Chi-Square	27.207	2	.0000
Improvement	11.107	1	.0009
Goodness of Fit	173.704	171	.4280

Classification Table for NINETO

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	40	37	51.95%
Worked less than	1	21	77	78.57%
			Overall	66.86%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
AGE	-.0486	.0238	4.1620	1	.0413	-.0957	.9526
EMPSTAT	-1.3370	.3625	13.6030	1	.0002	-.2216	.2626
PREADD	.8319	.2699	9.4975	1	.0021	.1781	2.2977
Constant	.8218	.7963	1.0650	1	.3021		

Model with Age, Employment Status, Previous Address, and Work Experience

	Chi-Square	df	Significance
-2 Log Likelihood	201.286	170	.0507
Model Chi-Square	34.991	3	.0000
Improvement	7.784	1	.0053
Goodness of Fit	171.238	170	.4589

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	43	34	55.84%
Worked less than	1	20	78	79.59%
			Overall	69.14%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
AGE	-.0935	.0306	9.3160	1	.0023	-.1760	.9107
EMPSTAT	-1.4310	.3753	14.5369	1	.0001	-.2303	.2391
PREADD	.7762	.2692	8.3125	1	.0039	.1635	2.1732
WORKEXP	.0134	.0050	7.1257	1	.0076	.1473	1.0135
Constant	1.4737	.8594	2.9405	1	.0864		

square for the subsequent model which contained four predictors(χ^2=34.991; df=3,175; p=.0000) indicates that it does predict who will turnover prior to completing training.

The incremental value of the additional variables added through forward stepwise selection was assessed by the improvement statistic which is the change in -2LL (-2 * log of the likelihood) between models and tests the null hypothesis that the variables added are zero. The Improvement statistic between the models indicates that the coefficients for each additional variable (i.e., employment status: improvement = 16.101, p =.0001; previous address: improvement = 11.107, p = .0009; work experience: improvement = 7.784, p = .0053) significantly add to the model.

Additional evidence of the usefulness of this model is shown by comparing the percentage correctly predicted to complete training by the model to the base rate. Of the total 175 subjects included in the logistic regression analysis forty-four percent worked more than ninety days and completed the training period. In contrast, of the sixty-three subjects predicted to complete training by the model, sixty-eight percent were correctly identified, a very substantial increase over the base rate.

The resulting model indicates that in comparison to those who were likely to leave before completion of training, those who stayed were more likely to be relatively older, have less work experience, have a previous address relatively close to the plant, and were employed prior to hire.

In order to further assess the relationship between exploratory predictors and turnover, the bivariate relationships between turnover and each of the exploratory items not included in the omnibus model were examined. This analysis found three additional variables significantly related to turnover. First, a logistic regression analysis of turnover on sex was significant (x^2=5.548; df=1,880; p=.0185; B=.3444) indicating that men are more likely to turnover before completing training than women.

A second variable related to turnover was duration on last job. A logistic regression analysis of turnover on duration resulted in a significant negative relationship between these variables (x^2=5.718; df=1,872; p=.0168; B= -.0074). This finding indicates that those with relatively more months on their last job are less likely to turnover.

Scores on the Wonderlic were the third variable with a significant relationship to turnover. The logistic regression analysis of turnover on Wonderlic scores indicates that those with higher scores are less likely to turnover (χ^2=14.278; df=1,814; p=.0002; B= -.0547).

Because of legal, as well as ethical, concerns age and sex are not predictors that can be utilized for selection purposes. Table 4g contains a revised model which excludes age. Family responsibility was excluded because it did not significantly contribute to the model in the previous analysis. The exploratory variables were examined for entry into the model through forward stepwise selection. Previous address, employment status, and Wonderlic scores were entered on successive steps. The resulting model also predicts turnover as indicated by the model chi-square (χ^2=30.272; df=3,361; p<.0000). This model is also practically useful in that fifty-eight percent of subjects predicted to complete training by the model were correctly identified. Stated differently, assuming an adequate supply of applicants, use of the model would enable the organization to increase the percentage of long tenure hires from the current base rate of forty-five percent to fifty-eight percent, a very meaningful improvement.

Table 4g

Logistic Regression Analysis: 90 Day Turnover with Wonderlic, Employment Status and Previous Address

Initial Model with Constant

	Chi-Square	df	Significance
-2 Log Likelihood	496.653	360	.0000
Goodness of Fit	361.000	360	.4753

Classification Table for NINETO

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	0	162	.00%
Worked less than	1	0	199	100.00%
			Overall	55.12%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
Constant	.2057	.1058	3.7789	1	.0519		

Model with Previous Address

	Chi-Square	df	Significance
-2 Log Likelihood	477.402	359	.0000
Model Chi-Square	19.251	1	.0000
Improvement	19.251	1	.0000
Goodness of Fit	359.706	359	.4796

		Predicted		
		Worked more than	Worked less than	
Observed		0	1	%Correct
Worked more than	0	126	36	77.78%
Worked less than	1	120	79	39.70%
			Overall	56.79%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
PREADD	.6796	.1637	17.2450	1	.0000	.1752	1.9731
Constant	-.7631	.2504	9.2908	1	.0023		

Table 4g continued
Logistic Regression Analysis: 90 Day Turnover with Wonderlic, Employment Status and Previous Address

Model with Employment Status and Previous Address

	Chi-Square	df	Significance
-2 Log Likelihood	470.618	358	.0001
Model Chi-Square	26.035	2	.0000
Improvement	6.784	1	.0092
Goodness of Fit	360.302	358	.4559

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	60	102	37.04%
Worked less than	1	38	161	80.90%
			Overall	61.22%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
EMPSTAT	-.5826	.2245	6.7329	1	.0095	-.0976	.5584
PREADD	.6649	.1655	16.1348	1	.0001	.1687	1.9444
Constant	-.5153	.2686	3.6813	1	.0550		

Model with Employment Status, Previous Address, and Wonderlic Scores

	Chi-Square	df	Significance
-2 Log Likelihood	466.381	357	.0001
Model Chi-Square	30.272	3	.0000
Improvement	4.237	1	.0396
Goodness of Fit	361.778	357	.4196

Observed		Predicted: Worked more than 0	Predicted: Worked less than 1	%Correct
Worked more than	0	79	83	48.77%
Worked less than	1	57	142	71.36%
			Overall	61.22%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
WONDRLIC	-.0451	.0220	4.1837	1	.0408	-.0663	.9559
EMPSTAT	-.5556	.2259	6.0493	1	.0139	-.0903	.5737
PREADD	.7031	.1680	17.5081	1	.0000	.1767	2.0201
Constant	.4107	.5231	.6163	1	.4324		

Validity Coefficients and Population Shrinkage Estimates.

Murphy (1983) states that the need to cross-validate sample results is clear to applied psychologists. However, because of disadvantages associated with single sample cross-validation designs, Murphy (1983) and Schmitt, Coyle, and Rauschenberger (1977) recommend the use of formulas which estimate the shrinkage of the validity coefficient in the population. These shrinkage estimates allow for at least equal estimates of population validities to those obtained when using cross-validation designs, as well as, allowing for more stable estimation of regression weights because all data are used to generate these weights.

Table 5 shows the resulting validity coefficients and estimates of the shrinkage in the population for the model containing age, employment status, previous address, and months of work experience from Table 4f. In addition, Table 5 also includes shrinkage estimates for the model with employment status, previous address, and Wonderlic (age excluded) from Table 4g. The column labeled Sample Multiple R is the correlation between actual group membership in the sample and group membership predicted by the relevant model. The Squared Sample Multiple R is the proportion of

Table 5
Validity Coefficients and Shrinkage Estimates

Model with Age, Employment Status, Previous Address, and Work Experience

	Sample Multiple R	Squared Sample Multiple R	Population Multiple R	Squared Pop. Multiple R
NINETO	.3407 (p<.001)	.1161	.2635	.0694

Model with Employment Status, Previous Address, and Wonderlic Scores

	Sample Multiple R	Squared Sample Multiple R	Population Multiple R	Squared Pop. Multiple R
NINETO	.2059 (p<.001)	.0424	.1538	.0236

variability accounted for by the model in question. The last two columns, labeled Population Multiple R and Squared Population Multiple R, utilize the Lord-Nicholson estimation formula (Schmitt et al., 1977) to estimate the shrunken correlation of each model when applied to the population.

Examination of Table 5 indicates that the model with age, employment status, previous address, and months of work experience ($R=.3407$, $p<.001$) and the model without age ($R=.2059$, $p<.001$) significantly predict the probability of turnover before completion of training.

Hypothesis #2

The second hypothesis was that employees who leave voluntarily versus involuntarily will differ on biodata items. To test this hypothesis, a logistic regression analysis of voluntariness of turnover on biodata items was used to predict which employees would leave voluntarily rather than involuntarily. The sample included the 702 employees who terminated and whose reason for leaving was recorded. The probability of leaving voluntarily was calculated for each subject. If the probability was greater than .5 subjects were predicted to leave voluntarily, and if the estimated probability was less than .5 subjects were predicted to leave involuntarily.

Based on past research sex, age, education, and tenure were initially entered into the logistic regression equation. As before, the remaining biodata items were examined for entry using forward stepwise selection.

The significance of each biodata item in the preliminary model was assessed by examining each coefficient's Wald statistic. Past research indicates that in contrast to voluntary leavers, involuntary leavers are more likely to be male, older, less educated, and have more tenure. Therefore, the Wald statistics for the coefficient for gender (male = 1 and female = 0), age, and tenure were predicted to be negative and significant, while the coefficient for years of education was predicted to be positive and significant. The direct effect of the remaining biodata items on voluntariness of leaving was less clear and was included on an experimental basis.

Results Hypothesis #2.

The results for the second hypothesis are reported in Table 6. The model contains the four variables shown by previous research to predict who will leave voluntarily versus involuntarily. However, the chi-square for the initial model (χ^2=5.338; df=4,335; p=.2544) indicates that the model does not effectively predict this criterion. In addition, none of the Wald Statistics for the predictors in the equation were significant indicating that the coefficient for each variable was not different from zero.

Separate logistic regression analyses of voluntariness of turnover on each predicted variable (i.e., education, tenure, sex, age) were also not significant, indicating that these predictors were not related to voluntariness of turnover. In addition, once education, tenure, sex, and age were removed no variables were added to the model through forward stepwise selection beyond the constant. These findings do not support a relationship between biodata variables and whether an employee leaves voluntarily or

Table 6
Logistic Regression Analysis Voluntary v. Involuntary Turnover

Initial Model

	Chi-Square	df	Significance
-2 Log Likelihood	396.025	330	.0073
Model Chi-Square	5.338	4	.2544
Improvement	5.338	4	.2544
Goodness of Fit	335.692	330	.4028

Observed		Predicted Involuntary I	Predicted Voluntary V	Percent Correct
Involuntary	I	2	94	2.08%
Voluntary	V	1	238	99.58%
			Overall	71.64%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
EDUCAT	-.1894	.1119	2.8630	1	.0906	-.0464	.8275
TENURE	-.0001	.0002	.2938	1	.5878	.0000	.9999
SEX	-.3918	.2725	2.0673	1	.1505	-.0130	.6759
AGE	-.0132	.0178	.5497	1	.4584	.0000	.9869
Constant	3.9286	1.4559	7.2817	1	.0070		

involuntarily.

Hypothesis #3

In order to test the third hypothesis, that voluntary versus involuntary leavers will differ on performance, a T-Test of mean performance for voluntary and involuntary leavers was performed. Voluntary leavers were predicted to have significantly higher levels of job performance than involuntary leavers.

Table 7

Performance Differences Between Voluntary and Involuntary Leavers

REVIEW1 First Review

	Number of Cases	Mean	Standard Deviation	Standard Error
Involuntary	142	17.0634	1.479	.124
Voluntary	190	17.6123	1.396	.101

Pooled Variance Estimate

t Value	Degrees of Freedom	2-Tail Prob.
-3.46	330	.001

REVIEW2 Second Review

	Number of Cases	Mean	Standard Deviation	Standard Error
Involuntary	85	17.4882	1.435	.156
Voluntary	128	18.1328	1.559	.138

Pooled Variance Estimate

t Value	Degrees of Freedom	2-Tail Prob.
-3.05	211	.003

REVIEW3 Third Review

	Number of Cases	Mean	Standard Deviation	Standard Error
Involuntary	56	17.9286	1.701	.227
Voluntary	105	18.2524	1.715	.167

Pooled Variance Estimate

t Value	Degrees of Freedom	2-Tail Prob.
-1.14	159	.254

LASTREV Last Review

	Number of Cases	Mean	Standard Deviation	Standard Error
Involuntary	144	16.7326	1.848	.154
Voluntary	198	17.8258	1.718	.122

Pooled Variance Estimate

t Value	Degrees of Freedom	2-Tail Prob.
-5.63	340	.000

Results Hypothesis #3.

The results for hypothesis three are displayed in Table 7. T-tests of mean performance for the first, second, third, and final performance reviews reveal that with the exception of the third review, voluntary leavers had higher performance ratings than involuntary leavers (Review1 $t=-3.46$, $p=.001$; Review2 $t=-3.05$, $p=.003$; Review3 $t=-1.14$, $p=.254$; Lastrev $t=-5.63$, $p=.000$) as predicted.

Hypothesis #4

The final hypothesis, that functional and dysfunctional voluntary leavers will differ on biodata items, was also analyzed using logistic regression. In this scenario, for the subset of 198 employees who left voluntarily, education level, age, similar experience, nervous tension, and dominance were inserted into the logistic regression equation using forced entry. Based on the performance research by Rothstein et al. (1990) with the exception of nervous tension, dysfunctional leavers were predicted to have higher scores on these items than functional leavers. Dysfunctional leavers were predicted to have lower levels of nervous tension than functional leavers.

The Wald statistics for the coefficients for education level, age, similar experience, and dominance were predicted to be negative where the dependent variable was coded "1" and "0" for functional and dysfunctional leavers, respectively. Nervous tension was predicted to be positively related to functionality. Because of limited previous research on the direct effect of the remaining biodata items on functionality of leavers, these items were included on an exploratory basis and were examined for entry into the existing equation in a forward stepwise manner.

The probability of being a functional leaver was estimated for each former employee. Those with an estimated probability greater than .5 were predicted to be a functional leaver, while those with an estimated probability less than .5 were predicted to be dysfunctional.

Results Hypothesis #4.

Table 8 contains the results from the logistic regression analysis of biodata items on functionality of turnover. The initial model contains all variables previously shown to be related to higher performance and effectiveness (i.e., education, age, similar experience, dominance, nervous tension). The chi-square for this model (χ^2=15.877; df=5,63; p=.0072) and classification table (82.54% correctly classified) indicate that this model does

Table 8
Logistic Regression Analysis Functional vs. Dysfunctional Turnover

Initial Model

	Chi-Square	df	Significance
-2 Log Likelihood	55.521	57	.5307
Model Chi-Square	15.877	5	.0072
Improvement	15.877	5	.0072
Goodness of Fit	56.024	57	.5117

Observed		Predicted Dysfunctional D	Predicted Functional F	Percent Correct
Dysfunctional	D	45	2	95.74%
Functional	F	9	7	43.75%
			Overall	82.54%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
EDUCAT	-1.1803	.6734	3.0716	1	.0797	-.1225	.3072
SIMEXPER	-.2180	.2210	.9738	1	.3237	.0000	.8041
AGE	-.0256	.0794	.1035	1	.7477	.0000	.9748
NERV TENSION	-.0616	.1193	.2664	1	.6057	.0000	.9403
DOMINANCE	-.2999	.1472	4.1537	1	.0415	-.1737	.7409
Constant	16.9431	8.7876	3.7175	1	.0538		

Revised Model

	Chi-Square	df	Significance
-2 Log Likelihood	163.123	130	.0260
Model Chi-Square	2.649	4	.6181
Improvement	2.649	4	.6181
Goodness of Fit	134.792	130	.3689

Observed		Predicted Dysfunctional D	Predicted Functional F	Percent Correct
Dysfunctional	D	94	0	100.00%
Functional	F	41	0	0.00%
			Overall	69.63%

Variable	B	S.E.	Wald	df	Sig	R	Exp(B)
EDUCAT	-.0838	.1968	.1813	1	.6702	.0000	.9196
SIMEXPER	-.0131	.0132	.9852	1	.3209	.0000	.9870
NERV TENSION	-.0358	.0695	.2646	1	.6070	.0000	.9649
DOMINANCE	.0521	.0690	.5694	1	.4505	.0000	1.0535
Constant	.3420	2.6131	.0171	1	.8959		

predict the probability of those who will be functional versus dysfunctional leavers.

However, with only sixty-three subjects and five predictors the subject to predictor ratio was such that substantial shrinkage is expected. Age, the predictor associated with the most missing data (N=121) was removed in order to increase sample size. A non-significant relationship was also found in a separate logistic regression analysis of turnover on age (χ^2=.065, p=.7985). The revised model, also included in Table 8, contains the model chi-square (χ^2=2.649; df=4,135; p=.6181) which indicates that this model, while the sample size was sufficient, does not significantly predict the probability of being a functional leaver. In addition, none of the Wald Statistics for the predictors in the equation were significant--indicating that the coefficients for each variable were not different from zero.

As before, separate logistic regression analyses of functionality of turnover on each predicted variable (i.e., education, similar experience, age, nervous tension, dominance) were conducted. None were found to be significant. Once these variables were removed no variables were added to the model through forward stepwise selection beyond the constant. These findings are not supportive of a relationship between biodata variables and whether an employee will be a functional or dysfunctional leaver.

Discussion

Hypothesis 1: Most Likely to Complete Initial Training

The results of this study have turned up some interesting findings that lead to some useful implications regarding biodata and turnover prior to completion of training. The statistical model with the variables identified by past research as related to turnover (i.e., family responsibility, similar experience, age, personality variables, mechanical interest) was not significant. However, two of the variables in the model had significant bivariate relationships with turnover.

Both age and level of family responsibility were found to be negatively related to turnover as predicted. Applicants with more family responsibility (i.e., married and at least one dependent) and those who are relatively older are more likely to complete the training period.

As reported earlier, when predictors unrelated to turnover were removed, exploratory variables were allowed to enter the model through forward stepwise selection (see Table 4f). The analysis revealed that, in addition to being older, those less likely to turnover were employed prior to being hired, had a previous address close to the plant, and had less work experience.

In order to identify a usable selection model that does not contain items which are legally questionable, the data were re-analyzed without age (see Table 4g). Once age was removed, Wonderlic was allowed to enter the model through forward stepwise selection and work experience no longer made an incremental contribution to the model. This analysis revealed that those less likely to turnover were employed prior to being hired, had a previous address close to the plant, and had higher scores on the Wonderlic.

The final model contained employment status, previous address, and Wonderlic scores. While not in the final model, three additional variables were bivariately related to ninety-day turnover. These included duration on last job, gender, and as reported earlier family responsibility. While the explanation for the unexpected relationships between specific biodata variables (i.e., prior employment status, previous address, gender, duration, and aptitude scores) and turnover is not clear, consideration of additional factors may shed some light.

First, although aptitude scores were not hypothesized to be related to turnover, a significant negative relationship was found indicating that those with higher aptitude scores are less likely to turnover. This finding does make sense considering that typically cognitive ability is related to performance (Hunter & Hunter, 1984) and performance is negatively related to turnover. Therefore, cognitive ability is negatively related to turnover.

Upon closer examination, the negative relationship between turnover and aptitude appears to be moderated by voluntariness of turnover. A logistic regression analysis of turnover on Wonderlic scores reveals that the relationship holds up for voluntary leavers (χ^2=3.963, df=1, p=.0465) but not for involuntary leavers (χ^2=.772, df=1, p=.3795). The fact that those with higher Wonderlic scores are less likely to turnover voluntarily during the training period suggests that aptitude helps new employees perform at higher levels, making them less likely to quit as reported by McEvoy and Casico (1987) and Stumpf and Dawley (1981).

A second relationship not predicted by past research indicated that the farther an employee's previous address was from the plant the more likely the employee was to turnover. This finding may indicate that those with a previous address farther from the plant have fewer ties to the community surrounding the facility and are, therefore, more likely to leave and go to another community or return home to family and friends.

Although previous research has not fully explored the relationship between turnover and employment status at time of hire, the current study found that new employees who leave a previous job to go to work for the current organization were less likely to turnover than those who were unemployed at the time of hire. This relationship is logical from the stand point that an individual who was employed at the time of hire at least had demonstrated the basic skills required to obtain and hold a job and had a real choice.

An alternative explanation for the relationship between turnover and employment status at time of hire is that those who leave a job to take another have more invested in the new job. This increased investment comes from giving up a job and, therefore, those who have more invested in a new position are more likely to stay.

Two predictors not in the final model held unexpected bivariate relationships with turnover. First, male employees are more likely to turnover than female employees.

Further examination revealed that this relationship held for those with low levels of family responsibility (χ^2=.4870, df=1, p=.0285), but not for those with high levels of family responsibility (χ^2=.2128, df=1, p=.4899). This result would indicate that gender is not related to turnover for employees who are married and have at least one child. However, among single employees without children, men leave at a higher rate than women.

A plausible explanation for the moderating effect of family responsibility on the relationship between gender and turnover may lie in company benefits. The company in the study offers a substantial benefits package including family medical and dental coverage, life insurance and survivor benefits, as well as 401(K) and pension plans. Employees with higher levels of family responsibility need these benefits and are motivated to stay in order to gain the fringe benefits which accompany the job. This finding is true for both males and females.

On the other hand, men with lower family responsibility are more likely to turnover than females. This finding may be explained by the opportunities perceived to be available to these employees. The subjects in this study were in an "unskilled" job market. Ninety-eight percent of new hires in the current organization filled entry-level, unskilled positions. These types of jobs often have a physical component. Men may perceive that they are more capable of performing these jobs and believe they have more options to pursue upon leaving. Additionally, many of these unskilled labor positions, such as construction laborers, pay a premium based on the physical nature of the jobs in order to attract employees. However, while paying a higher hourly wage rate, these physically demanding entry level positions typically do not have benefits such as medical insurance--which would be important to employees with high levels of family responsibility.

Second, the finding that employees with a longer duration in months on their last job were less likely to turnover is consistent with the theory of Owens (Mael, 1991) that the best predictor of future behavior is past behavior. It is logical that employees who were able to hold a job for a relatively longer period of time in the past have the propensity to stay longer in their current job.

The major practical implication which emerged from the data concerning biodata and turnover is the identification of a prediction model to aid in the selection of new employees. This model consists of employment status, previous address, and Wonderlic scores. Age was removed for ethical reasons and to prevent charges of employment discrimination. Utilization of these predictors offers the potential to increase the percentage of long-tenure hires from the current base rate of forty-five percent to fifty-eight percent. This figure represents a twenty-nine percent increase in the retention rate, an increase with very substantial monetary implications for the organization.

Hypothesis 2: Those Most Likely to Leave Voluntarily

The theoretical model proposed by Stump and Dawley (1981) and Wells and Muchinsky (1985) to differentiate voluntary and involuntary leavers on biodata variables suggests that voluntary leavers will be younger, female, more educated, and have less tenure. However, none of these variables contributed significantly to the prediction of voluntary versus involuntary turnover. Thus, the current study does not support the findings previously reported in the literature.

Hypothesis 3: Voluntariness and Performance

While voluntary and involuntary leavers did not differ on biodata items, as predicted, they did vary on performance (McEvoy & Casico, 1987; Stumpf & Dawley, 1981; Wanous et al., 1979; Wells & Muchinsky, 1985). Voluntary leavers had significantly higher levels of performance than involuntary leavers for the first, second, and last reviews. However, voluntary leavers did not have significantly higher performance on the third review--possibly explainable by the fact that the third review is used as a pass/fail review. Employees must pass the third review in order to become a regular employee. Those who are performing poorly may quit voluntarily before being terminated involuntarily for a poor third review. The finding that performance differences exist between voluntary and involuntary leavers is important in that it adds to what is known about the voluntariness of turnover by confirming previous research.

Hypothesis 4: Those Most Likely to be a Functional Leaver

Based on the performance effectiveness research (Porter & Steers, 1973; Rothstein et al., 1990) biodata items were predicted to differentiate functional from dysfunctional leavers. Functional leavers were predicted to be less educated, relatively younger, and have less similar experience, more nervous tension, and less dominance. However, the model as a whole was not able to significantly predict functionality nor were any of the variables individually. Thus, at this point, those employees whose leaving is viewed as positive by the organization cannot be identified based on the variables suggested by past research.

Organization specific variables not examined in the current study may have affected hypothesized relationships in hypotheses one, two, and four. The first variable which may have affected predicted relationships is the local economic conditions. The geographic area surrounding the facility from which the majority of applicants was drawn has experienced relatively low unemployment for several years. Unemployment rates near four percent (often regarded as full employment) are not uncommon. When unemployment rates are low jobs are more plentiful, thereby providing employees more options to pursue if their current position does not meet expectations. Thus, when employees become discouraged with an employment situation for whatever reason and have several other employment options to select from, they are more likely to turnover despite their standing on biodata items.

A second factor which may have affected hypothesized relationships is the ambient temperature in the facility during summer months. The temperature during these months can linger in the ninety to one hundred degree range for days or weeks. Over the fourteen year period covered by the study, forty percent of the turnover has occurred during the three hottest months of the year. Thus, employees are likely to quit because of uncommonly hot working conditions regardless of individual factors reflected in biodata items.

A third variable affecting the relationship between biodata and various turnover criteria is an unusually hostile labor-management relationship. While the facility is nonunion, four union organizing attempts by two different labor unions have occurred during the period covered by the study. These organizing campaigns are very emotional and stressful for employees who are exposed to conflicting versions of the issues by the company and union organizers. The stress, hostility, and mistrust created by these campaigns between contrasting groups of employees remain long after an organizing attempt is over. Therefore, employees may leave in order to avoid the conflict and stress regardless of traits reflected in biodata.

In addition to the situational moderators discussed above, multicollinearity may have also affected the findings regarding the predicted relationships. Multicollinearity exists when there are high correlations among predictors (Stevens, 1986). For example, several of the aptitude measures used to predict turnover had correlations of .40 or higher. The presence of multicollinearity confounds the effects of the predictors making it difficult to determine the importance of a given predictor because of the high correlation between them. Multicollinearity helps explain why certain findings in the literature were not confirmed.

In conclusion, there are several useful findings emerging from this study. First, in regard to the selection of new hires that will remain long enough to complete training, a model was developed having the potential to increase the percentage of new hires who complete training from forty-five percent to fifty-eight percent.

Secondly, the knowledge base on biodata and turnover has been expanded by underscoring the importance of potential situational moderators of the relationship between biodata and various types of turnover. While disappointing, biodata items were unable to differentiate between voluntary and involuntary leavers or functional and dysfunctional leavers as previous research found. Economic conditions, working conditions, and adversarial labor-management relationships may reduce or eliminate the usefulness of biodata variables to predict various types of turnover. In addition, these moderators explain the inconsistent and nonrobust findings in the literature. However, voluntary and involuntary leavers were found to differ on performance in support of past research.

The present study suggests two areas for future research. One area requiring additional investigation concerns the unexpected relationship between Wonderlic scores, employment status, previous address, duration on last job and gender with turnover. Such research would serve to confirm that these relationships do in fact exist. Biodata research exploring situational moderators such as the effect of labor-management relationships, working conditions, and economic conditions on turnover is also suggested to aid in the understanding of these variables.

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Appendix

Correlation Matrix

Correlations:	AGE	SEX	EDUCAT	WORKEXP	DURATION	SIMEXPER
AGE	1.0000**	-.1660**	.0399	.5994**	.3082**	.3865**
SEX	-.1660**	1.0000**	-.0250	.0330	-.0156	-.0119
EDUCAT	.0399	-.0250	1.0000**	.0001	.0250	.1772**
WORKEXP	.5994**	.0330	.0001	1.0000**	.5453**	.3892**
DURATION	.3082**	.0156	.0250	.5453**	1.0000**	.1163**
SIMEXPER	.3865**	-.0119	.1772**	.3892**	.1163**	1.0000**
EMPSTAT	-.0393	.0188	.0397	.0555	.0715	-.0083
MARTIAL	.3308**	.1734**	.0252	.2133**	.1467**	.1176**
DEPENDS	.2703**	.1629**	-.0175	.1083**	.0276	.0605
SHIFT	-.0517	.0691	-.0472	-.0189	.0543	-.0503
STARTRAT	.0366	.0660	.2142**	.1594**	.0536	.1921**
WONDRLIC	-.0146	.0354	.2254**	.0028	-.0334	.0571
PRO1	.0978	.0235	.2543**	.0210	-.0250	.0415
PRO2	.2788**	-.0053	.2577**	.2141**	.1064*	.2112**
PRO3	.2048*	.1007*	.1616**	.0853	.0276	.1655**
PRO4	.1080	-.0743	.2528**	.0629	.0179	.1202*
PRO5	-.0366	-.1504**	.0663	.0353	-.0213	.0205
PRO6	-.0531	.3698**	.1502**	.0417	-.0051	.0623
PRO7	.0893	.0397	.0431	.0465	-.0232	.0123
PRO10	-.1576	-.1021*	.0641	-.0564	-.1046*	.0544
PRO11	.0547	.1621**	.0104	.0171	.0030	-.0039
PRO12	.0677	-.1266*	-.0775	-.0315	.0244	.0180
PRO13	-.0191	-.3691**	-.0303	-.0546	-.0305	.0434
PRO16	-.1856*	.2068**	.1096*	.0717	-.0803	.0397
REVIEW1	.1057	-.0566	.0646	.0911	.0969	.0432
REVIEW2	.0446	-.0603	.0255	.0673	.0700	-.0285
REVIEW3	.0737	-.0473	.0485	.1336	.0892	.0490
LASTREV	.3047**	-.0965	.1026*	.1166*	.1195*	.0817
CUREMP	.3343**	-.0381	.0980*	.1594**	.1644**	.1225**
VOLNESS	.0282	-.0645	.0014	.0446	-.0074	-.0043
TENURE	.1823**	-.1352**	-.0078	.0069	.0645	.0685
FUNALITY	.0232	.1237	-.0515	.0275	-.0965	-.0524
CURADD	-.0560	-.0153	.0410	-.0414	-.0071	.1045**
PREADD	-.0235	.0695	.0807	.1329*	-.0536	.1829**
EMPS	.0736	-.0148	-.0278	.1233**	-.0381	.0379
OFFSHIFT	-.0625	-.0005	-.0776*	-.0580	.0413	-.0668
MECHINT	-.0992	.5115**	.1677*	.0715	-.0214	.0660
COMPETE	.0276	.3620**	-.0669	.0251	.0330	-.0331
NERVTEN	.0465	.0520	.1302	.0208	-.0947	.0118
SOCIABLE	-.2788*	.0860	.0671	-.0732	-.1559*	.0877
EMOTMAT	.1190	.2018**	.0113	.0201	.0337	-.0021
DOMINANT	.1139	.1473*	-.0748	-.0045	.0158	.0655
WORKMOT	-.2262*	.2523**	.1308	-.1065	-.1042	-.1177
NINETO	-.0901	.0797*	-.0606	.0046	-.0824*	-.0533
FAMRES	.3748**	-.2307**	.0283	.2186**	.1250**	.1220**

Correlations:	EMPSTAT	MARTIAL	DEPENDS	SHIFT	STARTRAT	WONDRLIC
AGE	-.0393	.3308**	.2703**	-.0517	.0366	-.0146
SEX	-.0188	-.1734**	-.1629**	-.0691	.0660	.0354
EDUCAT	.0397	.0252	-.0175	-.0472	.2142**	.2254**
WORKEXP	.0555	.2133**	.1083**	-.0189	.1594**	.0028
DURATION	.0715	.1467**	.0276	.0543	.0536	-.0334
SIMEXPER	-.0083	.1176**	.0605	-.0503	.1921**	.0571
EMPSTAT	1.0000**	-.0095	.0281	-.0162	.0011	.0653
MARTIAL	-.0095	1.0000**	.4129**	.0264	.0350	.0291
DEPENDS	.0281	.4129**	1.0000**	.0779*	-.1289**	-.0153
SHIFT	-.0162	-.0264	-.0779*	1.0000**	.1915**	-.0628
STARTRAT	.0011	.0350	-.1289**	.1915**	1.0000**	.0991*
WONDRLIC	.0653	.0291	-.0153	.0628	.0991*	1.0000**
PRO1	.0934	.0173	-.0389	-.0127	.1664**	.5535**
PRO2	.0608	.1087*	.0392	-.0768	.1874**	.4952**
PRO3	-.0046	-.0090	-.0338	.0377	.1914**	.4076**
PRO4	.0474	.0715	-.0137	-.0579	.1690**	.4387**
PRO5	.0406	.0594	.0473	-.0475	.0801	.2368**
PRO6	.0129	.0014	-.0553	.0342	.2014**	.1298*
PRO7	.0342	.0359	-.0039	-.0001	.0005	-.0493
PRO10	-.0685	.0186	.0158	-.0757	.0537	-.0998*
PRO11	.0379	.0004	.0105	.0538	.0590	-.0936
PRO12	.0146	.0385	-.0152	-.0177	-.1137*	-.0607
PRO13	.0555	.0586	-.0056	-.0972	-.1473**	-.0803
PRO16	.0066	-.1053*	-.1464**	.0437	.1000	.0397
REVIEW1	.0393	-.0338	.0259	-.0273	-.0735	.0236
REVIEW2	.0078	-.0037	.0989	.0356	-.0900	.0194
REVIEW3	.0307	.0568	.0820	-.0914	-.0143	.0314
LASTREV	.1002	.0606	.0773	-.0588	.0251	.0221
CUREMP	.1090**	.1180**	.0956*	-.0770*	.2456**	.0864*
VOLNESS	.0501	-.0076	-.0323	.0991*	.0867	.0046
TENURE	.1140**	.0731	.0976*	-.1199**	-.3116**	.0815
FUNALITY	-.1344	.0380	-.0833	.1530	.2201**	-.0427
CURADD	-.0049	-.0225	-.0479	-.0446	-.0468	.0470
PREADD	-.0872	-.0815	.0696	.0027	.0748	.0718
EMPS	-.0619	.0528	-.0394	.0683	.2372**	-.0251
OFFSHIFT	.0107	-.0157	-.0570	.7985**	.0413	-.0367
MECHINT	.0353	.0017	.0657	.0424	.2297**	.1587*
COMPETE	-.0136	.0624	.0528	.1661	.1473	-.0965
NERVTEN	.0838	.0689	-.0313	.0153	.0773	-.0545
SOCIABLE	-.0644	-.0043	-.0243	-.0831	-.0198	-.0938
EMOTMAT	-.0236	.0244	.0307	.0408	.0847	-.1438*
DOMINANT	-.0248	.0737	-.0034	-.0650	-.1537*	-.0418
WORKMOT	-.0364	-.1477*	.1858**	.0562	.1460	.0216
NINETO	-.1230**	-.0236	-.0652	.1145**	.2013**	-.1328**
FAMRES	.0196	1.0000**	.8580**	-.0634	-.0809	.0118

Correlations:	PRO1	PRO2	PRO3	PRO4	PRO5	PRO6
AGE	.0978	.2788**	.2048*	.1080	-.0366	-.0531
SEX	.0235	-.0053	.1007*	-.0743	-.1504**	.3698**
EDUCAT	.2543**	.2577**	.1616**	.2528**	.0663	.1502**
WORKEXP	.0210	.2141**	.0853	.0629	.0353	.0417
DURATION	-.0250	.1064*	.0276	.0179	-.0213	-.0051
SIMEXPER	.0415	.2112**	.1655**	.1202*	.0205	.0623
EMPSTAT	.0934	.0608	-.0046	.0474	.0406	.0129
MARTIAL	.0173	.1087*	-.0090	.0715	.0594	-.0014
DEPENDS	-.0389	.0392	-.0338	-.0137	.0473	.0553
SHIFT	-.0127	-.0768	.0377	-.0579	-.0475	.0342
STARTRAT	.1664**	.1874**	.1914**	.1690**	.0801	.2014**
WONDRLIC	.5535**	.4952**	.4076**	.4387**	.2368**	.1298*
PRO1	1.0000**	.4426**	.3771**	.5160**	.2238**	.0941
PRO2	.4426**	1.0000**	.4108**	.4974**	.0926	.0901
PRO3	.3771**	.4108**	1.0000**	.4290**	.1431**	.0798
PRO4	.5160**	.4974**	.4290**	1.0000**	.1952**	-.0199
PRO5	.2238**	.0926	.1431**	.1952**	1.0000**	-.0207
PRO6	.0941	.0901	.0798	-.0199	-.0207	1.0000**
PRO7	-.0137	-.0253	-.0249	-.0489	.0185	.1491**
PRO10	-.0562	-.1102*	-.0955	-.0566	.0390	.0873
PRO11	-.1297**	-.0948	-.0202	-.0755	-.0663	.1448**
PRO12	-.1241*	.0665	-.0652	-.0860	.0343	-.1331**
PRO13	-.0654	.0394	-.0867	.0658	.0570	-.1932**
PRO16	.0398	.0176	.0415	-.0143	.0014	.2279**
REVIEW1	.0392	.0637	-.0014	.0693	.0472	.0073
REVIEW2	-.0169	.0002	.0447	-.0074	-.0123	-.0768
REVIEW3	.0187	.0535	.0639	.0007	-.0718	.0394
LASTREV	.0924	.0826	.0526	.0546	.0450	-.0095
CUREMP	.0637	.0495	.0432	-.0246	.0448	.0063
VOLNESS	.1133	-.0066	.0072	.0304	.1242*	-.0568
TENURE	.0153	-.0174	-.0176	-.0149	.0207	-.0145
FUNALITY	-.0052	-.0023	.0999	.0521	.1208	.0031
CURADD	.0698	.0681	.0260	.0234	-.0039	-.0284
PREADD	.0701	.0566	.0016	.0695	-.0432	.0829
EMPS	-.0211	-.0134	-.0756	-.1243*	.0661	-.0073
OFFSHIFT	-.0068	-.0811	.0214	-.0449	-.0448	.0390
MECHINT	.1136	.1053	.0811	-.0576	-.0687	.9361**
COMPETE	-.0497	-.1019	.0427	.1291	-.1801*	.1069
NERVTEN	-.0157	-.0465	-.0502	-.0832	.0685	.2010**
SOCIABLE	-.0599	-.1194	-.0912	-.0200	.0404	.1346
EMOTMAT	-.1765*	-.0972	-.0416	-.0867	-.1028	.1790*
DOMINANT	-.1091	-.0556	-.0870	.0886	.0408	-.1878**
WORKMOT	.0601	-.0740	-.0026	.0510	.0006	.2587**
NINETO	-.0706	-.0554	.0191	.0122	.0177	.0168
FAMRES	-.0133	.0905	-.0387	.0541	.0645	-.0324

Correlations:	PRO7	PRO10	PRO11	PRO12	PRO13	PRO16
AGE	.0893	-.1576	.0547	.0677	-.0191	-.1856*
SEX	.0397	-.1021*	.1621**	-.1266*	-.3691**	.2068**
EDUCAT	.0431	.0641	.0104	-.0775	-.0303	.1096*
WORKEXP	.0465	-.0564	.0171	-.0315	-.0546	-.0717
DURATION	-.0232	-.1046*	.0030	.0244	-.0305	-.0803
SIMEXPER	.0123	.0544	-.0039	.0180	.0434	-.0397
EMPSTAT	.0342	-.0685	-.0379	-.0146	-.0555	-.0066
MARTIAL	.0359	.0186	-.0004	.0385	-.0586	-.1053*
DEPENDS	-.0039	.0158	.0105	-.0152	-.0056	-.1464**
SHIFT	-.0001	-.0757	.0538	-.0177	-.0972	.0437
STARTRAT	.0005	-.0537	.0590	-.1137*	-.1473**	.1000
WONDRLIC	-.0493	-.0998*	-.0936	-.0607	-.0803	.0397
PRO1	.0137	-.0562	-.1297**	-.1241*	-.0654	.0398
PRO2	.0253	-.1102*	-.0948	-.0665	-.0394	-.0176
PRO3	.0249	-.0955	-.0202	-.0652	-.0867	.0415
PRO4	.0489	-.0566	-.0755	-.0860	.0658	-.0143
PRO5	.0185	.0390	-.0663	.0343	.0570	.0014
PRO6	.1491**	.0873	.1448**	-.1331**	-.1932**	.2279**
PRO7	1.0000**	.0715	.3207**	.0019	.0168	.0419
PRO10	.0715	1.0000**	.1213*	-.0962	.0479	.3033**
PRO11	.3207**	.1213*	1.0000**	.0061	-.0241	.1001*
PRO12	.0019	-.0962	.0061	1.0000**	.1362**	-.1101*
PRO13	.0168	.0479	-.0241	.1362**	1.0000**	-.1511**
PRO16	.0419	.3033**	.1001*	.1101*	-.1511**	1.0000**
REVIEW1	-.0202	.0202	.0526	.0882	.0781	-.0917
REVIEW2	-.0838	-.0500	-.0490	.1247	.0515	-.1681*
REVIEW3	-.0365	.0106	-.0113	.0754	.0221	-.1452
LASTREV	-.0068	-.0512	.0624	.0511	.1066	-.1173
CUREMP	-.0041	-.1185*	.0364	.0068	.0068	-.0528
VOLNESS	.0223	.0055	-.0681	-.0139	.1309*	-.0732
TENURE	-.0157	-.0589	-.0114	.0849	.0813	-.1156*
FUNALITY	-.0509	-.0503	.1077	.0535	.0350	.0335
CURADD	.0073	.0006	.0598	.0821	.0484	-.0515
PREADD	-.0041	.1078	-.0779	-.0578	.0245	.0978
EMPS	.0202	-.0748	.0100	.0163	.0342	-.0756
OFFSHIFT	.0111	-.0427	.0672	-.0077	.0614	.0132
MECHINT	.1661*	.0848	.1841*	-.2011**	-.2775**	.2876**
COMPETE	.0293	-.0091	.0882	-.0813	.9752**	.1743*
NERVTEN	.9639**	.1040	.4511**	-.0084	.0015	.1246
SOCIABLE	.0897	.9466**	.1871**	-.1459*	.0915	.3614**
EMOTMAT	.4383**	.1557*	.9450**	-.0102	-.0290	.0987
DOMINANT	-.0065	-.1307	-.0170	.9461**	.1247	-.1088
WORKMOT	.0523	.3684**	.1069	-.1258	-.1593*	.9425**
NINETO	.0003	.0667	-.0056	-.0454	-.0409	.0465
FAMRES	.0300	.0361	-.0152	.0151	-.0309	-.1453*

Correlations:	REVIEW1	REVIEW2	REVIEW3	LASTREV	CUREMP	VOLNESS
AGE	.1057	.0446	.0737	.3047**	.3343**	-.0282
SEX	-.0566	-.0603	-.0473	-.0965	-.0381	-.0645
EDUCAT	.0646	.0255	.0485	.1026*	.0980*	.0014
WORKEXP	.0911	.0673	.1336	.1166*	.1594**	.0446
DURATION	.0969	.0700	.0892	.1195*	.1644**	-.0074
SIMEXPER	.0432	-.0285	.0490	.0817	.1225**	-.0043
EMPSTAT	.0393	.0078	-.0307	.1002	.1090**	.0501
MARTIAL	-.0338	-.0037	.0568	.0606	.1180**	-.0076
DEPENDS	.0259	.0989	.0820	.0773	.0956*	-.0323
SHIFT	-.0273	.0356	-.0914	-.0588	-.0770*	.0991*
STARTRAT	-.0735	-.0900	-.0143	.0251	.2456**	.0867
WONDRLIC	.0236	.0194	.0314	.0221	.0864*	.0046
PRO1	.0392	-.0169	.0187	.0924	.0637	.1133
PRO2	.0637	-.0002	.0535	.0826	.0495	-.0066
PRO3	-.0014	.0447	.0639	.0526	.0432	.0072
PRO4	.0693	-.0074	.0007	.0546	-.0246	.0304
PRO5	.0472	-.0123	-.0718	.0450	.0448	.1242*
PRO6	.0073	-.0768	.0394	-.0095	.0063	-.0568
PRO7	-.0202	-.0838	-.0365	-.0068	-.0041	.0223
PRO10	.0202	-.0500	.0106	-.0512	-.1185*	.0055
PRO11	.0526	-.0490	-.0113	.0624	.0364	-.0681
PRO12	.0882	.1247	.0754	.0511	.0068	-.0139
PRO13	.0781	.0515	.0221	.1066	.0068	.1309*
PRO16	.0917	-.1681*	-.1452	-.1173	.0528	-.0732
REVIEW1	1.0000**	.7110**	.6396**	.5719**	.0990	.1871**
REVIEW2	.7110**	1.0000**	.8031**	.4688**	.0861	.2054*
REVIEW3	.6396**	.8031**	1.0000**	.4774**	.0542	.0904
LASTREV	.5719**	.4688**	.4774**	1.0000**	.4290**	.2919**
CUREMP	.0990	.0861	.0542	.4290**	1.0000**	.
VOLNESS	.1871**	.2054*	.0904	.2919**	.	1.0000**
TENURE	.2489**	.2451**	.2353**	.4173**	.3511**	.0306
FUNALITY	-.3361**	-.2333*	-.2223	-.4704**	.	.
CURADD	.0086	.0342	.0923	-.0212	-.0352	.0113
PREADD	-.0283	-.0956	-.0540	-.2045**	-.2535**	.0880
EMPS	-.0499	-.0418	-.0442	.0190	.0145	.0178
OFFSHIFT	-.0025	.0328	.0483	-.0445	-.0692	.1007*
MECHINT	-.0477	-.1569	.0603	-.0099	.0007	-.0948
COMPETE	-.0202	-.0967	.1216	-.1205	.0034	.1336
NERVTEN	-.1124	-.1988	-.1489	-.0493	.0080	.0174
SOCIABLE	.0596	-.0691	.0497	-.0834	-.1432*	.0256
EMOTMAT	.0995	-.0460	-.0205	.0656	.0413	.1019
DOMINANT	.1186	.1482	.1062	.0941	.0071	.0052
WORKMOT	-.1361	.1916	-.1877	-.1242	-.0548	-.0863
NINETO	-.2993**	.2530**	.0305	-.3555**	-.3747**	.0124
FAMRES	.0194	.0735	.1179	.0966	.1507**	-.0507

Correlations:	TENURE	FUNALITY	CURADD	PREADD	EMPS	OFFSHIFT
AGE	.1823**	.0232	-.0560	-.0235	.0736	-.0625
SEX	-.1352**	.1237	-.0153	.0695	-.0148	-.0005
EDUCAT	-.0078	-.0515	.0410	.0807	-.0278	-.0776*
WORKEXP	.0069	.0275	-.0414	.1329*	.1233**	-.0580
DURATION	.0645	.0965	-.0071	-.0536	-.0381	.0413
SIMEXPER	.0685	.0524	.1045**	.1829**	.0379	.0668
EMPSTAT	.1140**	.1344	-.0049	-.0872	-.0619	.0107
MARTIAL	.0731	.0380	-.0225	-.0815	.0528	.0157
DEPENDS	.0976*	.0833	-.0479	-.0696	-.0394	-.0570
SHIFT	-.1199**	.1530	-.0446	.0027	.0683	.7985**
STARTRAT	-.3116**	.2201**	-.0468	.0748	.2372**	.0413
WONDRLIC	.0815	-.0427	.0470	.0718	-.0251	-.0367
PRO1	.0153	-.0052	.0698	.0701	-.0211	-.0068
PRO2	-.0174	-.0023	.0681	.0566	-.0134	-.0811
PRO3	-.0176	.0999	.0260	.0016	-.0756	.0214
PRO4	-.0149	.0521	.0234	.0695	-.1243*	-.0449
PRO5	.0207	.1208	-.0039	-.0432	.0661	-.0448
PRO6	-.0145	.0031	-.0284	.0829	-.0073	.0390
PRO7	-.0157	-.0509	.0073	.0041	.0202	.0111
PRO10	-.0589	-.0503	.0006	.1078	-.0748	-.0427
PRO11	-.0114	-.1077	-.0598	.0779	.0100	.0672
PRO12	.0849	.0535	.0821	-.0578	.0163	-.0077
PRO13	.0813	.0350	.0484	-.0245	.0342	-.0614
PRO16	.1156*	-.0335	-.0515	.0978	.0756	.0132
REVIEW1	.2489**	-.3361**	.0086	-.0283	.0499	-.0025
REVIEW2	.2451**	-.2333*	.0342	-.0956	-.0418	.0328
REVIEW3	.2353**	-.2223	.0923	-.0540	-.0442	-.0483
LASTREV	.4173**	-.4704**	-.0212	-.2045**	.0190	-.0445
CUREMP	.3511**	.	-.0352	-.2535**	.0145	-.0692
VOLNESS	.0306	.	.0113	.0880	.0178	.1007*
TENURE	1.0000**	-.4408**	.0228	-.2093**	-.1668**	-.0918*
FUNALITY	-.4408**	1.0000**	-.0256	.0000	.1219	.0199
CURADD	.0228	-.0256	1.0000**	.1871**	-.1579**	-.0680
PREADD	-.2093**	.0000	.1871**	1.0000**	.1028	.0086
EMPS	-.1668**	.1219	-.1579**	.1028	1.0000**	.0384
OFFSHIFT	-.0918*	.0199	-.0680	.0086	.0384	1.0000**
MECHINT	-.0024	-.0545	-.0350	.0909	.0364	.0359
COMPETE	-.1002	-.0214	.0181	.2134	.1046	.1125
NERVTEN	-.0281	-.1517	.0267	.0540	.0560	.0139
SOCIABLE	-.0940	.0041	.0163	.1405	-.0860	-.0443
EMOTMAT	.0108	-.1607	-.0985	-.1213	.0217	.0577
DOMINANT	.0864	.0265	.1297	-.0313	-.0175	-.0542
WORKMOT	-.1082	-.0136	-.1122	.1595	-.0973	.0318
NINETO	-.5615**	.8779**	-.0385	.2168**	.1784**	.0601
FAMRES	.1224*	-.0376	-.0657	-.1495*	-.0182	-.0264

Correlations:	MECHINT	COMPETE	NERVTEN	SOCIABLE	EMOTMAT	DOMINANT
AGE	-.0992	.0276	.0465	-.2788*	.1190	.1139
SEX	.5115**	.3620**	.0520	-.0860	.2018**	-.1473*
EDUCAT	.1677*	-.0669	.1302	.0671	.0113	-.0748
WORKEXP	.0715	.0251	.0208	-.0732	.0201	-.0045
DURATION	-.0214	.0330	-.0947	-.1559*	.0337	.0158
SIMEXPER	.0660	-.0331	.0118	.0877	-.0021	.0655
EMPSTAT	.0353	-.0136	.0838	-.0644	-.0236	-.0248
MARTIAL	.0017	.0624	.0689	-.0043	.0244	.0737
DEPENDS	-.0657	-.0528	-.0313	-.0243	.0307	-.0034
SHIFT	.0424	.1661	.0153	-.0831	.0408	-.0650
STARTRAT	.2297**	.1473	.0773	-.0198	.0847	-.1537*
WONDRLIC	.1587*	-.0965	-.0545	-.0938	-.1438*	-.0418
PRO1	.1136	-.0497	-.0157	-.0599	-.1765*	-.1091
PRO2	.1053	-.1019	-.0465	-.1194	-.0972	-.0556
PRO3	.0811	.0427	-.0502	-.0912	-.0416	-.0870
PRO4	-.0576	-.1291	-.0832	-.0200	-.0867	-.0886
PRO5	-.0687	-.1801*	.0685	.0404	-.1028	.0408
PRO6	.9361**	.1069	.2010**	.1346	.1790*	-.1878**
PRO7	.1661*	.0293	.9639**	.0897	.4383**	-.0065
PRO10	.0848	-.0091	.1040	.9466**	.1557*	-.1307
PRO11	.1841*	.0882	.4511**	.1871**	.9450**	-.0170
PRO12	-.2011**	-.0813	-.0084	-.1459*	-.0102	.9461**
PRO13	-.2775**	-.9752**	.0015	.0915	-.0290	.1247
PRO16	.2876**	.1743*	.1246	.3614**	.0987	-.1088
REVIEW1	-.0477	-.0202	-.1124	.0596	.0995	.1186
REVIEW2	-.1569	-.0967	-.1988	-.0691	-.0460	.1482
REVIEW3	.0603	-.1216	-.1489	.0497	-.0205	.1062
LASTREV	-.0099	-.1205	-.0493	.0834	.0656	.0941
CUREMP	.0007	.0034	.0080	.1432*	.0413	.0071
VOLNESS	-.0948	-.1336	-.0174	.0256	-.1019	.0052
TENURE	-.0024	-.1002	-.0281	-.0940	.0108	.0864
FUNALITY	-.0545	-.0214	-.1517	.0041	-.1607	-.0265
CURADD	-.0350	.0181	.0267	.0163	-.0985	.1297
PREADD	.0909	.2134	.0540	.1405	-.1213	-.0313
EMPS	.0364	.1046	.0560	-.0860	.0217	-.0175
OFFSHIFT	.0359	.1125	.0139	-.0443	.0577	-.0542
MECHINT	1.0000**	.2431	.2381*	.1443	.2174*	-.2714**
COMPETE	.2431	1.0000**	.1088	.0569	.0905	-.0626
NERVTEN	.2381*	.1088	1.0000**	.1197	.5987**	-.0035
SOCIABLE	.1443	.0569	.1197	1.0000**	.2411*	-.1981*
EMOTMAT	.2174*	.0905	.5987**	.2411*	1.0000**	-.0434
DOMINANT	-.2714**	-.0626	-.0035	-.1981*	-.0434	1.0000**
WORKMOT	.3259**	.1405	.1202	.4496**	.0832	-.1306
NINETO	.0000	-.0456	.0065	.0939	-.0388	-.0306
FAMRES	-.0474	.0080	.0593	-.0148	.0005	.0305

Correlations:	WORKMOT	NINETO	FAMRES
AGE	-.2262*	-.0901	.3748**
SEX	.2523**	.0797*	-.2307**
EDUCAT	.1308	-.0606	.0283
WORKEXP	-.1065	.0046	.2186**
DURATION	.1042	-.0824*	.1250**
SIMEXPER	.1177	-.0533	.1220**
EMPSTAT	.0364	-.1230**	.0196
MARTIAL	.1477*	-.0236	1.0000**
DEPENDS	.1858**	-.0652	.8580**
SHIFT	.0562	.1145**	-.0634
STARTRAT	.1460	.2013**	-.0809
WONDRLIC	.0216	-.1328**	.0118
PRO1	.0601	-.0706	-.0133
PRO2	-.0740	-.0554	.0905
PRO3	-.0026	.0191	-.0387
PRO4	-.0510	.0122	.0541
PRO5	-.0006	-.0177	.0645
PRO6	.2587**	.0168	-.0324
PRO7	.0523	-.0003	.0300
PRO10	.3684**	.0667	.0361
PRO11	.1069	-.0056	-.0152
PRO12	-.1258	-.0454	.0151
PRO13	-.1593*	-.0409	.0309
PRO16	.9425**	.0465	.1453*
REVIEW1	-.1361	-.2993**	.0194
REVIEW2	-.1916	-.2530**	.0735
REVIEW3	-.1877	.0305	.1179
LASTREV	-.1242	-.3555**	.0966
CUREMP	-.0548	-.3747**	.1507**
VOLNESS	-.0863	.0124	-.0507
TENURE	-.1082	-.5615**	.1224*
FUNALITY	-.0136	.8779**	-.0376
CURADD	-.1122	-.0385	-.0657
PREADD	.1595	.2168**	-.1495*
EMPS	-.0973	.1784**	-.0182
OFFSHIFT	.0318	.0601	-.0264
MECHINT	.3259**	.0000	-.0474
COMPETE	.1405	-.0456	.0080
NERVTEN	.1202	.0065	.0593
SOCIABLE	.4496**	.0939	-.0148
EMOTMAT	.0832	-.0388	.0005
DOMINANT	-.1306	.0306	.0305
WORKMOT	1.0000**	.0536	-.1815*
NINETO	.0536	1.0000**	-.0841
FAMRES	-.1815*	.0841	1.0000**

Minimum pairwise N of cases: 51 1-tailed Signif: * - .01 ** - .001